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Research Article

Characterization of the Electrical Energy Consumption of Some Areas Supplied by the Lomé a Interconnection Station of the CEET in Lomé, Togo: Analysis and Discussion

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Abstract: This study aims to analyze the electricity consumption of Greater Lomé (Togo), a critical issue in view of the increasing needs and imperatives of energy transition. We used 63,943 data samples from the Togo Electric Energy Company (CEET), covering eight sites spread across three municipalities over a period of 84 months (2018-2024). A multidimensional statistical approach was used to evaluate active power through nine indicators, including central tendency, dispersion and distribution shape measures (skewness and kurtosis). The results show three distinct distribution profiles: symmetrical, asymmetrical and random. The maximum consumption observed varies from 5.643 MW to 9.900 MW, while the average consumption is between 2.800 MW and 5.620 MW. The analysis reveals similarities between the sites: Four sites (ADIDOGOME, DOGBEAVOU, CASABLANCA, GARAGE CENTRAL) show averages between 3.000 MW and 3.700 MW; three sites (AVENOU, GAKLI, N'DANIDA) show almost identical averages, around 4 to 5 MW. The ADEWI site records the lowest average (2.000 to 3.000 MW). Given the shape indicators, it is difficult to determine the average production power required per site. For this purpose, it is necessary to try in future work the use of artificial intelligence to create models and make good decisions.

Keywords: Analysis, Characterization, Electrical Energy, Interconnection Station, power Consumption, Statistical Parameters

Introduction

In today's environment of new information and communication technology, combined with industrialization and home automation, the demand for electrical energy continues to grow every day. This is driving research efforts to find solutions for the production of electrical energy (Guenoukpati, 2022; Kouzou, 2010). Given that primary energy sources are diverse and abundant depending on the environment, there is a need to review the systems for injecting electricity into the grid. The problem associated with this production stems from fossil primary energy sources (Manzoor *et al*., 2018; Saber and Venayamoorthy, 2010; Paria *et al*., 2014). These pollute the environment through their greenhouse gas emissions (Sarhan *et al*., 2023; Gift and Abiodun, 2021). In view of this, policies encourage large-scale electricity production from renewable primary sources. Examples include the Paris Climate Agreement and party conferences (Aoife *et al*., 2017; Tianyu *et al*., 2024; Ghezloun *et al*., 2017). For Africa, it is recommended to use solar photovoltaic, wind, and geothermal energy because oil, natural gas, and coal contribute to the rapid destruction of nature. They increase the risk of bush fires, heat waves, floods, tsunamis, etc. (Mohamed *et al*., 2019; Junxiang *et al*., 2024).

In addition to all of the above, there are several development plans in our regions. These include the division of countries into municipalities (Medewou *et al*., 2019). That said, since 2018, prefectures have been divided into municipalities in Togo, a humid, coastal country in West Africa bordered by Burkina Faso to the north, the Atlantic Ocean to the south, Benin to the east, and Ghana to the west (Electricity Sector Regulatory Authority, 2020). The country is

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supplied with electricity through imports, which accounted for approximately 63% of its total electricity consumption in 2020 (Norbert, 2019). According to the Electricity Sector Regulatory Authority (ARSE), this figure may have decreased with recent initiatives to increase local electricity production (PND, 2018). In Togo, only the Benin Electricity Community (CEB) is responsible for electricity transmission and the Togo Electricity Company (CEET) for electricity distribution (Komla *et al*., 2024a). Based on five economic regions, the country has 39 prefectures and 117 municipalities that contribute to local development. However, the economic development of each municipality is strongly linked to its self-sufficiency in electricity supply. In order to determine the amount of electricity needed to meet each municipality's needs, it is necessary to map their electricity requirements.

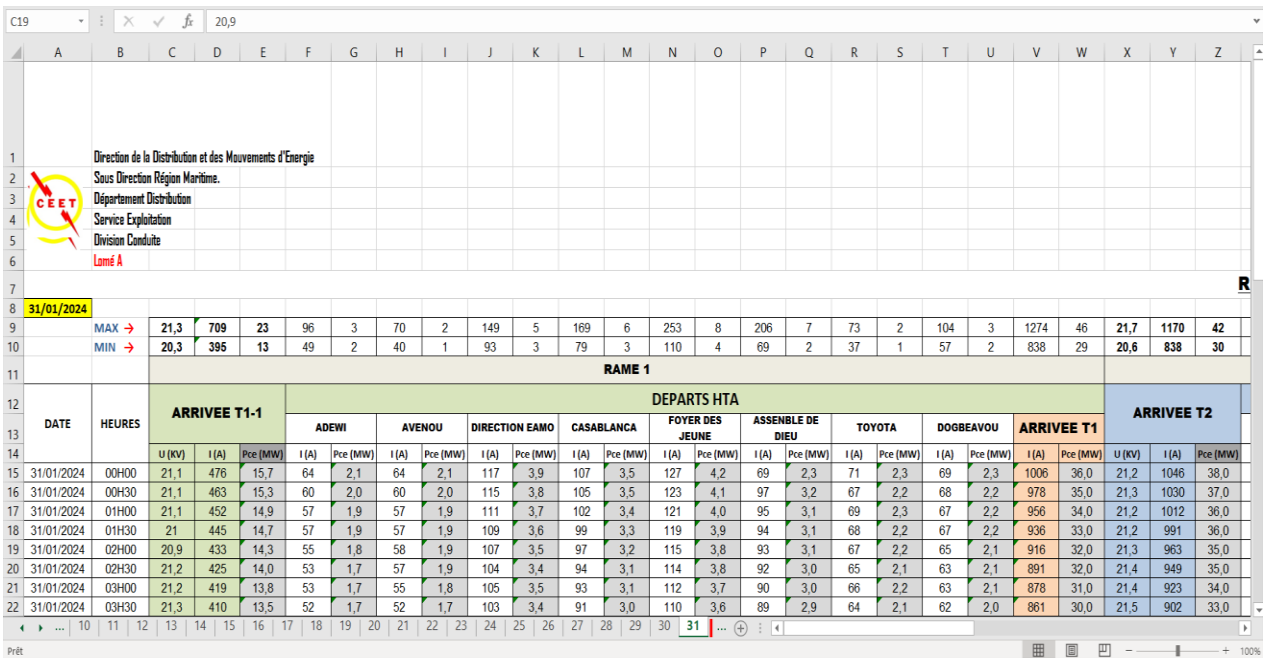
Furthermore, in order to determine the amount of electricity needed to meet the needs of each municipality, it is necessary to characterize their consumption. The aim of this study is therefore to characterize the consumption of a number of municipalities based on available data. The goal is to use an approach based on statistical analysis of the data to define a fixed electricity consumption value per municipality. To achieve this, the study takes into account eight (8) areas in three municipalities spread across the Greater Lomé administrative region, namely: ADEWI and GARAGE CENTRAL in the municipality of Golfe 3; DOGBEAVOU and N'DANIDA in the municipality of Golfe 4; and ADIDOGOME, AVENOU, CASABLANCA, and GAKLI in the municipality of Golfe 5. We will use consumption data collected over 84 months, or seven consecutive years, from January 1, 2018, to December 31, 2024. This data is collected by CEET at its distribution station in Lomé A. The statistical parameters used for data analysis are: Mean, median, mode, minimum, maximum, standard deviation, mean deviation, skewness, and kurtosis (Wang *et al*., 2022; Shuayb *et al*., 2023; Yates and Khan, 2024; Komla *et al*., 2024b). Data analysis for each site will first be carried out on a monthly basis for the seven years, then annually, and finally for all years combined in order to fully understand the consumption profile for effective decision-making.

The results of these analyses will give the leaders of each municipality a clear idea of how much power to generate in order to meet the electricity needs of their population, thereby contributing to their development in this regard.

Materials

In this work, we will use the operating data of CEET, collected at its LOME A distribution station. The active powers consumed from 2018 to 2024, from January to December, will be used. These data are often automatically recorded on the network via an Excel file with a half-hourly range as can be seen in Fig. 1.

In fact, each site is served by two feeders from different source stations. Thus, in the event of a breakdown on one of the feeders, the second is loaded to the maximum possible capacity to take over the maximum load from the faulty feeder.



Direction de la Distribution et des Mouvements d'Energie
Sous Direction Région Maritime.
Département Distribution
Service Exploitation
Division Conduite
Lomé A

31/01/2024

		RAME 1																							
DATE	HEURES	ARRIVEE T1-1			DEPARTS HTA: ADEWI		AVENOU		DIRECTION EAMO		CASABLANCA		FOYER DES JEUNE		ASSENBLE DE DIEU		TOYOTA		DOGBEAVOU		ARRIVEE T1		ARRIVEE T2		
		U (KV)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	I (A)	Pce (MW)	U (KV)	I (A)	Pce (MW)
	MAX →	21,3	709	23	96	3	70	2	149	5	169	6	253	8	206	7	73	2	104	3	1274	46	21,7	1170	42
	MIN →	20,3	395	13	49	2	40	1	93	3	79	3	110	4	69	2	37	1	57	2	838	29	20,6	838	30
31/01/2024	00H00	21,1	476	15,7	64	2,1	64	2,1	117	3,9	107	3,5	127	4,2	69	2,3	71	2,3	69	2,3	1006	36,0	21,2	1046	38,0
31/01/2024	00H30	21,1	463	15,3	60	2,0	60	2,0	115	3,8	105	3,5	123	4,1	97	3,2	67	2,2	68	2,2	978	35,0	21,3	1030	37,0
31/01/2024	01H00	21,1	452	14,9	57	1,9	57	1,9	111	3,7	102	3,4	121	4,0	95	3,1	69	2,3	67	2,2	956	34,0	21,2	1012	36,0
31/01/2024	01H30	21	445	14,7	57	1,9	57	1,9	109	3,6	99	3,3	119	3,9	94	3,1	68	2,2	67	2,2	936	33,0	21,2	991	36,0
31/01/2024	02H00	20,9	433	14,3	55	1,8	58	1,9	107	3,5	97	3,2	115	3,8	93	3,1	67	2,2	65	2,1	916	32,0	21,3	963	35,0
31/01/2024	02H30	21,2	425	14,0	53	1,7	57	1,9	104	3,4	94	3,1	114	3,8	92	3,0	65	2,1	63	2,1	891	32,0	21,4	949	35,0
31/01/2024	03H00	21,2	419	13,8	53	1,7	55	1,8	105	3,5	93	3,1	112	3,7	90	3,0	66	2,2	63	2,1	878	31,0	21,4	923	34,0
31/01/2024	03H30	21,3	410	13,5	52	1,7	52	1,7	103	3,4	91	3,0	110	3,6	89	2,9	64	2,1	62	2,0	861	30,0	21,5	902	33,0

Fig. 1: Excel file showing the recording of raw consumption data

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Indeed, each feeder covering a given area is subdivided into several branches, each branch serving a part of the targeted area. Thus, in the event of a failure on one of the branches, the part of the target area supplied by this branch is de-energized, therefore the consumption on the said feeder drops. If the failure occurs on two or three branches serving significant loads, the consumption drops considerably on this feeder, which means that we sometimes record consumption three (3) to five (5) times lower compared to normal consumption. In the distribution substation, the data is often automatically recorded on the network via an Excel file over a half-hourly range for each feeder. Since the feeders are not all created simultaneously, some have more load monitoring data than others. Thus, to carry out this study, we took care to process the raw data collected in the substation by considering only the active powers in Megawatt consumed on the sites whose data are available for the study period considered. Figure 2 shows the Excel sheet containing the processed data. This represents the active power in Megawatts consumed per area, for 84 months, from January 1, 2018 to December 31, 2024.

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	A	B	C	D	E	F	G	H	I	J	K
1	DATE	HEURE	AVENOU	ADEWI	GARAGE CENTRAL	CASABLANCA	GAKLI	DOGBEAVOU	N'DANIDA	ADIDOGOME	
418	2018-08-28 00:00:00	12H30	6,138	3,3	5,577	1,848	3,135	3,696	4,752	3,465	
419	2018-08-29 00:00:00	12H30	4,851	3,333	5,544	1,914	3,333	3,663	4,884	3,465	
420	2018-08-30 00:00:00	12H30	6,072	3,267	4,059	1,848	3,201	4,125	4,026	3,036	
421	2018-08-31 00:00:00	12H30	5,94	3,036	3,96	1,782	3,201	4,125	4,752	3,432	
422	2018-08-01 00:00:00	13H00	5,808	3,168	4,026	1,848	3,102	4,488	4,389	3,3	
423	2018-08-02 00:00:00	13H00	5,709	3,102	5,61	1,782	3,234	2,607	4,356	3,465	
424	2018-08-03 00:00:00	13H00	5,775	3,102	5,742	1,848	3,102	3,993	4,29	3,465	
425	2018-08-04 00:00:00	13H00	5,973	2,013	5,313	1,683	3,036	3,168	4,818	3,531	
426	2018-08-05 00:00:00	13H00	6,006	1,65	4,884	1,089	2,772	2,607	4,455	3,465	
427	2018-08-06 00:00:00	13H00	5,874	3,036	5,742	1,188	3,3	3,795	5,016	3,465	
428	2018-08-07 00:00:00	13H00	5,841	2,904	5,379	1,221	3,069	3,564	4,785	3,432	
429	2018-08-08 00:00:00	13H00	6,006	3,102	5,709	1,815	3,234	3,861	4,95	3,498	
430	2018-08-09 00:00:00	13H00	5,907	3,069	5,676	1,815	3,3	3,762	5,016	3,498	
431	2018-08-10 00:00:00	13H00	5,973	3,036	5,61	1,848	3,267	3,96	5,016	3,564	
432	2018-08-12 00:00:00	13H00	6,336	1,683	5,115	1,617	2,904	2,805	4,884	3,696	
433	2018-08-13 00:00:00	13H00	5,973	2,871	5,379	1,683	3,003	3,531	4,851	3,465	
434	2018-08-14 00:00:00	13H00	5,61	2,871	5,247	1,716	3,036	3,63	4,785	3,399	
435	2018-08-15 00:00:00	13H00	6,039	1,815	4,95	1,584	2,937	2,937	4,62	3,564	
436	2018-08-16 00:00:00	13H00	5,94	3,234	4,653	1,881	3,366	4,059	5,115	3,531	
437	2018-08-17 00:00:00	13H00	5,874	3,069	5,511	1,782	3,069	3,828	4,785	3,531	
438	2018-08-18 00:00:00	13H00	6,006	1,947	5,016	1,6665	2,871	3,036	4,785	3,696	
439	2018-08-19 00:00:00	13H00	6,369	1,683	4,917	1,551	2,805	2,64	4,785	3,531	
440	2018-08-20 00:00:00	13H00	5,907	3,201	5,841	1,881	3,3	3,894	4,917	3,63	
441	2018-08-21 00:00:00	13H00	6,27	1,716	5,115	1,584	3,003	2,739	4,785	3,597	
442	2018-08-22 00:00:00	13H00	5,94	3,036	5,544	1,716	3,003	2,739	4,62	3,465	
443	2018-08-23 00:00:00	13H00	4,158	2,805	4,422	1,749	3,003	3,234	4,455	3,333	
444	2018-08-24 00:00:00	13H00	5,94	2,739	5,016	1,65	3,036	3,102	4,554	3,267	
445	2018-08-25 00:00:00	13H00	6,171	1,881	5,049	1,485	2,838	2,937	4,653	3,432	

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Fig. 2: Excel sheet containing active power data in Megawatt (MW) consumed per site from 2018 to 2024

Methods

As a method, a statistical characterization on the consumed active power is presented, taking into account: The mean; the median; the mode; the Max and the Min; the standard deviation; the mean deviation; the Skewness and the Kurtosis. Some details on the method are presented in the following sections.

Table 1 summarizes the role and relevance of central tendency indicators (mean, median, mode and dispersion (min, max, standard deviation, mean deviation used in this study.

Skewness Coefficient (γ_1)

The skewness coefficient measures the asymmetry of the data distribution. Its expression is given by Eq. 6. Theoretically for normal distribution, Skewness = 0, If it is greater than zero, the distribution is spread to the right and if it is less than zero, the distribution is spread to the left.

Table 1: Summary of central tendency and dispersion indicators used in the study

Category	Indicator	Role	Relevance
Central tendency	Mean (μ), Eq. 1	Estimates the center of gravity of the data	Standard location measure for symmetric distributions. Sensitive to extreme values.
	Median	The central value of a distribution. 50% of the data are below and 50% are above	Extremely robust to outliers. Essential for skewed distributions
	Mode	The most frequent value in the dataset	Useful for detecting major peaks and describing multimodal or categorical distributions
Dispersion	Min and Max, Eq. 2 and Eq. 3	Sets the data limit values	Gives the total range; crucial for detecting anomalies and outliers
	Standard deviation (σ), Eq. 4	Measures the dispersion of data around the mean	Standard for quantifying variability. Fundamental for confidence intervals and tests
	Mean Absolute Deviation (MAD), Eq. 5	Measures the average distance of each point from the mean	Robust and intuitive measure of dispersion, less sensitive to outliers than standard deviation

Kurtosis Coefficient (γ_2)

The kurtosis coefficient indicates to what extent the tail of a distribution differs from the normal distribution. Indeed, the normal distribution, also called Gaussian distribution, is a continuous probability distribution characterized by its symmetry and its bell shape. The probability density function of a random variable " a " following a normal distribution is given by Eq. 7. The expression of the kurtosis coefficient is given by Eq.8. Theoretically for normal distribution, the Kurtosis = 3. Thus, if it is greater than 3, the distribution is less flattened than a Gaussian distribution and if it is less than 3, the distribution is more flattened than a Gaussian distribution:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} a_i \tag{1}$$

$$Max = \max(a_1, \dots, a_n) \tag{2}$$

$$Min = \min(a_1, \dots, a_n) \tag{3}$$

$$\sigma = \sqrt{\left(\frac{1}{n-1}\sum_{i=1}^{n}(a_i-\mu)^2\right)} \tag{4}$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |a_i - \mu| \tag{5}$$

$$\gamma_1 = \frac{\frac{1}{n}\sum_{i=1}^{n}(a_i-\mu)^3}{\sigma^3} \tag{6}$$

$$\gamma_2 = \frac{\frac{1}{n}\sum_{i=1}^{n}(a_i-\mu)^4}{\sigma^4} - 3 \tag{7}$$

$$f(a) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(a-\mu)^2}{2\sigma^2}} \tag{8}$$

Where:

a	Is the random variable
μ	Is the mean, which represents the central value of the data (MW)
n	Is total number of data in the sample
a_i	Is value of the $i-ème$ observation
σ	Is standard deviation (MW)
MAD	Is Mean absolute deviation (MW)
γ_1	Is Skewness coefficient
γ_2	Is Kurtosis coefficient

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Results

In this section, we will first present the monthly statistical results (January to December) for each site from 2018 to 2024, then the annual statistical results, and finally the cumulative statistical results for all seven years for each site. The values recorded in the tables are expressed in MW, with the exception of the skewness and kurtosis coefficients.

For reasons of ease and convenience related to reading the figures, Table 2 details the study periods considered and the codes assigned to the sites in question.

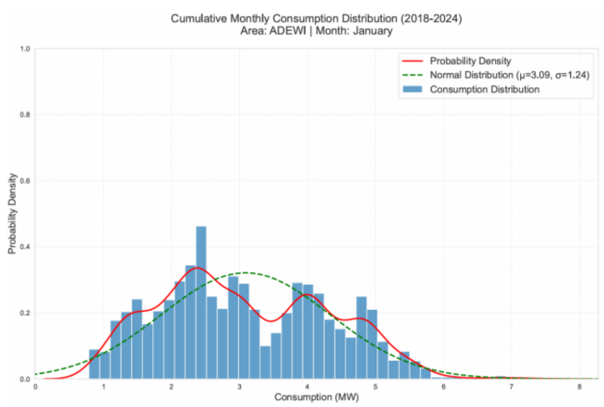
Table 3 and Fig. 3 present, respectively, the statistical results and the consumption evolution graphs for the months of January from 2018 to 2024 for each area.

Table 2: Details of study periods with assigned alphabets according to the sites considered

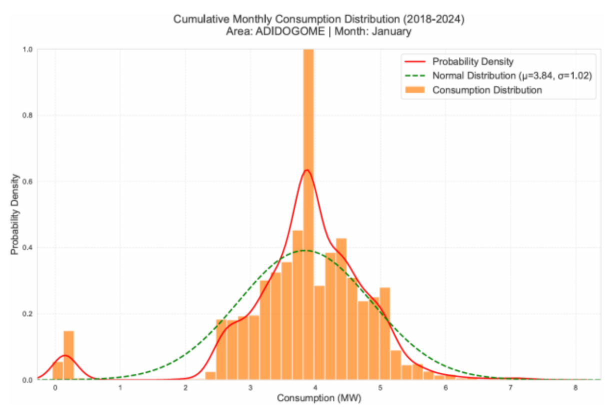
N°	Area	Code assigned	Graphical results and tables are presented	Months considered	Years considered
1	ADEWI	a	For each site considered, the analysis is based on Every month of the year, for all the years combined Every year, based on all the months combined All years and months combined	January February March April May June July August September November December	- 2018 - 2019 - 2020 - 2021 - 2022 - 2023 - 2024
2	ADIDOGOME	b			
3	AVENOU	c			
4	CASABLANCA	d			
5	DOGBEAVOU	e			
6	GAKLI	f			
7	GARAGE CENTRAL	g			
8	N’DANIDA	h			

Table 3: Statistical results for the months of January 2018-2024

	Statistical parameters									
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5498	3.090	2.937	2.409	0.792	7.524	1.241	1.054	0.270	-0.754
ADIDOGOME	5498	3.835	3.891	3.891	0.099	7.623	1.019	0.690	-1.303	4.181
AVENOU	5498	4.652	4.620	4.647	0.396	9.933	1.376	1.050	0.194	0.285
CASABLANCA	5498	3.424	3.267	2.475	0.429	6.138	1.078	0.909	0.335	-0.650
DOGBEAVOU	5498	3.515	3.300	3.300	0.429	8.900	1.326	1.084	0.382	-0.142
GAKLI	5498	4.892	4.917	5.544	0.726	9.042	1.276	0.995	-0.203	0.687
GARAGE CENTRAL	5498	3.896	3.902	3.902	0.396	8.283	1.276	1.059	0.079	-0.714
N'DANIDA	5498	4.309	4.191	3.663	0.363	8.217	0.837	0.673	0.409	0.682



(a)



(b)

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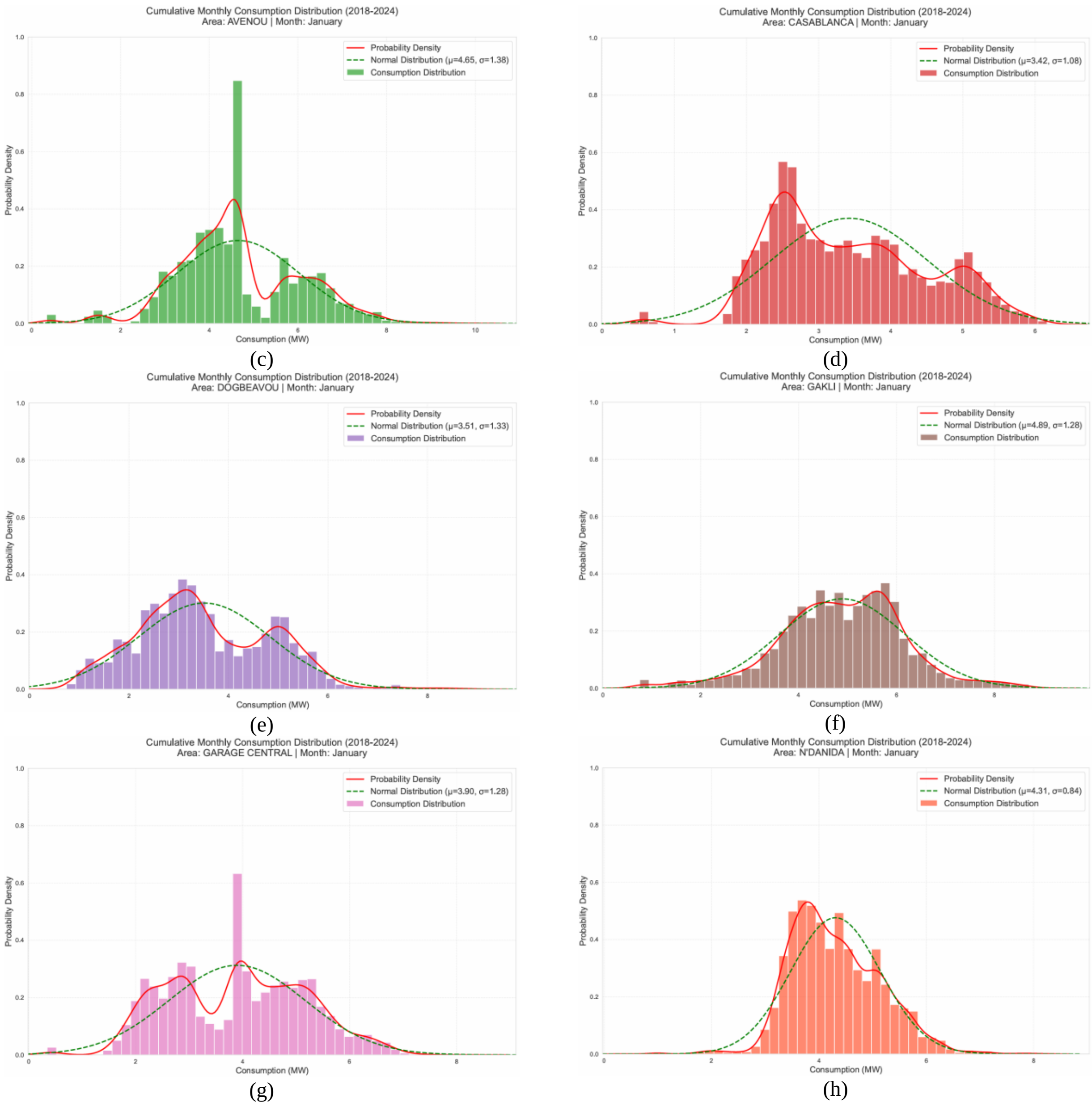

Fig. 3: Graphs of changes in consumption for the month of January for each area

The statistical results and distribution histograms of consumption for the months of February from 2018 to 2024 are shown in Table 4 and Fig. 4 respectively.

Table 4: Statistical results for the months of February from 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5020	2.979	2.937	3.194	0.825	8.000	1.029	0.835	0.346	-0.446
ADIDOGOME	5020	3.685	3.960	0.132	0.099	9.867	1.480	1.051	-0.903	1.502
AVENOU	5020	4.651	4.595	3.927	0.792	9.735	1.655	1.344	-0.210	-0.515
CASABLANCA	5020	3.651	3.597	3.655	0.396	6.864	1.113	0.964	0.012	-0.773
DOGBEAVOU	5020	4.409	4.417	4.417	0.330	8.943	1.096	0.778	-0.390	0.840
GAKLI	5020	4.980	5.247	5.280	0.363	9.669	1.563	1.183	-0.829	0.688
GARAGE CENTRAL	5020	4.146	4.290	4.752	0.561	7.953	1.279	1.058	-0.107	-0.363
N'DANIDA	5020	4.519	4.389	3.960	1.782	9.240	0.831	0.674	0.632	1.066

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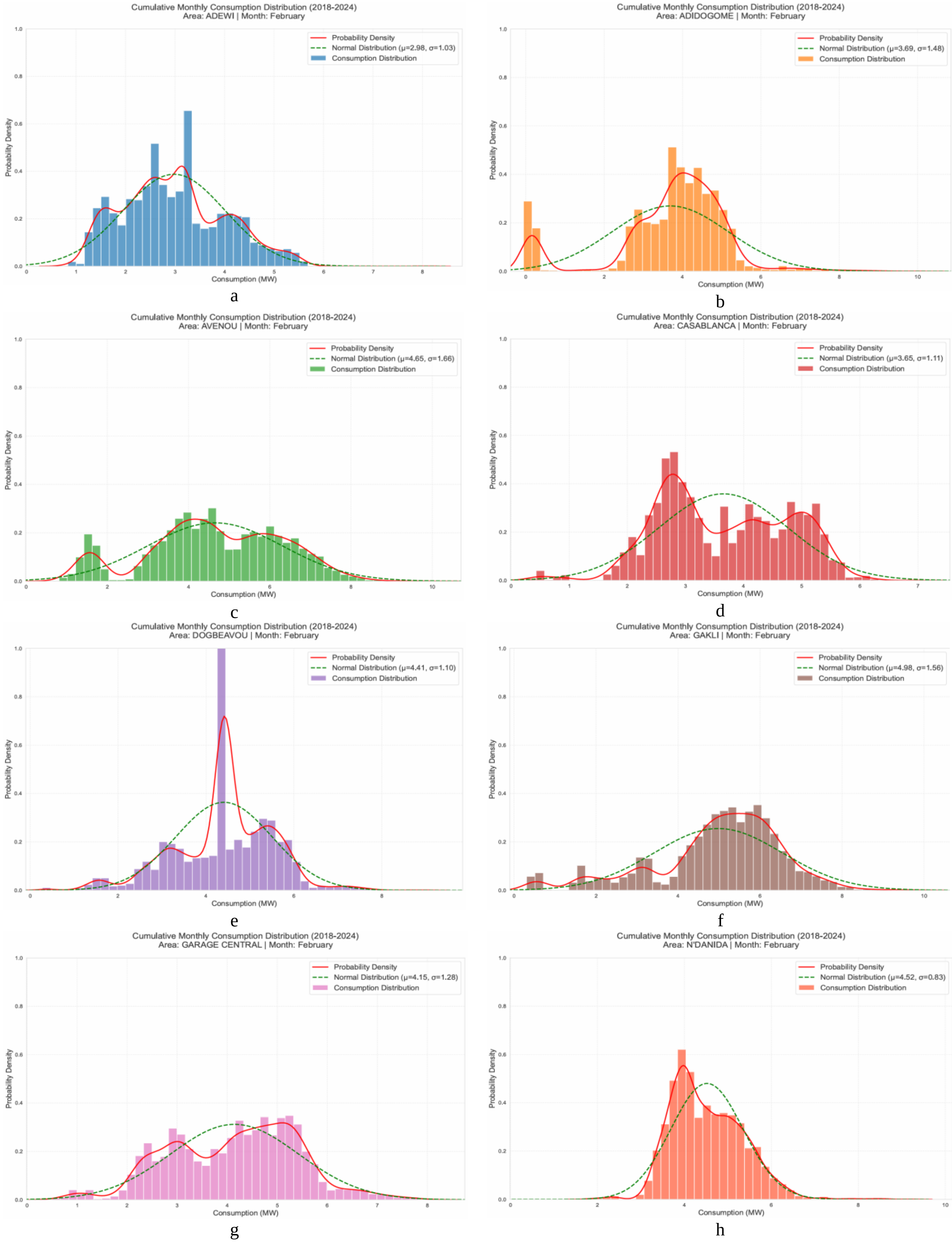


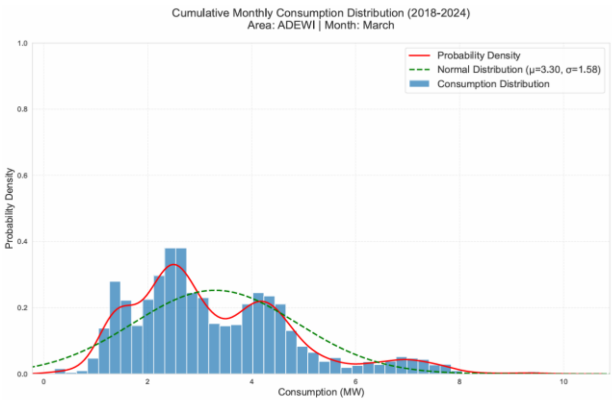
Fig. 4: Graphs of changes in consumption for the month of February for all areas

The statistical results for the months of March from 2018 to 2024 are presented in Table 5.

Table 5: Statistical results for the months of March 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5365	3.296	2.937	2.475	0.264	9.900	1.578	1.263	0.918	0.706
ADIDOGOME	5365	3.554	3.927	0.132	0.099	8.976	1.664	1.258	-0.753	0.316
AVENOU	5365	5.257	5.255	5.255	0.264	9.966	1.406	1.155	-0.367	0.273
CASABLANCA	5365	3.699	3.665	3.665	0.396	6.006	1.186	1.000	-0.009	-0.735
DOGBEAVOU	5365	4.198	3.993	3.168	0.132	9.900	1.731	1.430	0.168	-0.241
GAKLI	5365	5.392	5.412	5.280	0.264	9.570	1.189	0.855	-0.508	3.433
GARAGE CENTRAL	5365	4.179	4.202	4.202	0.132	8.085	1.222	0.968	-0.268	0.237
N'DANIDA	5365	4.467	4.389	3.960	0.297	9.405	0.877	0.710	-0.281	1.239

Figure 5 illustrates the distribution of consumption for the months of March from 2018 to 2024 across all areas.



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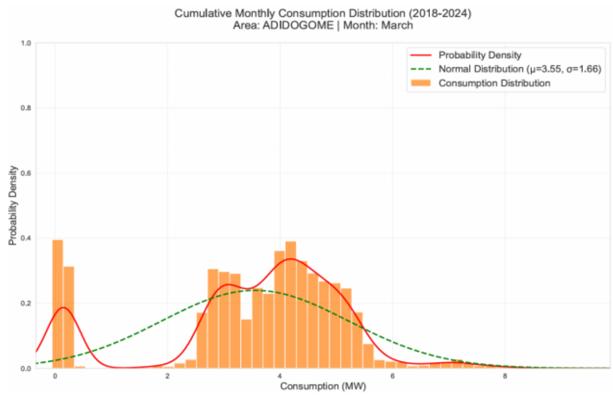

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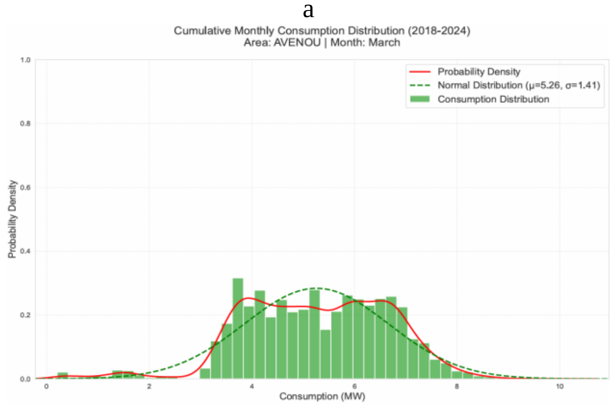

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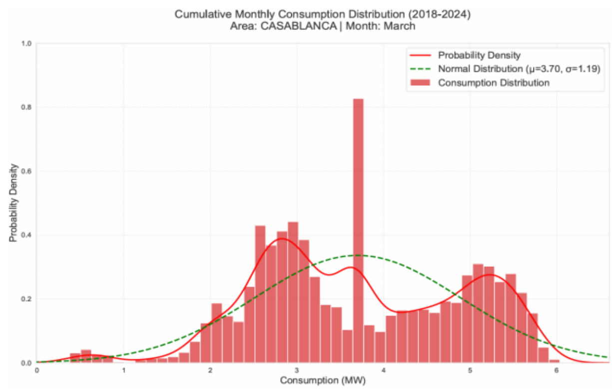

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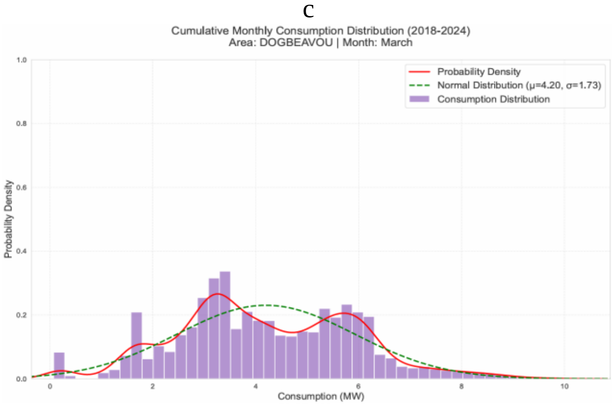

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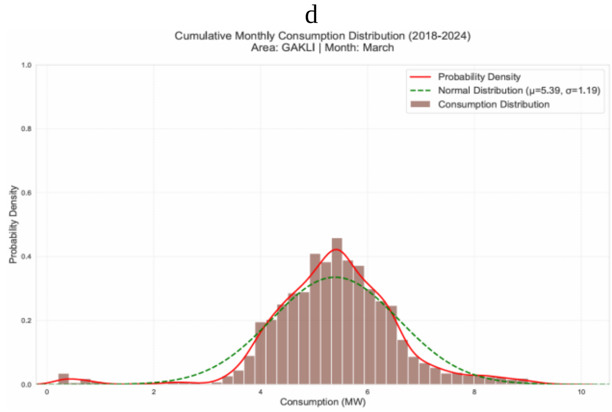

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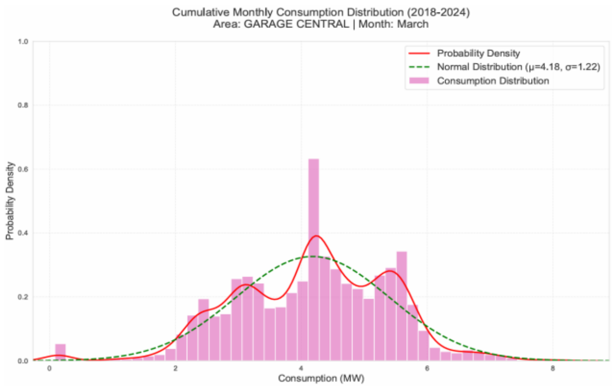

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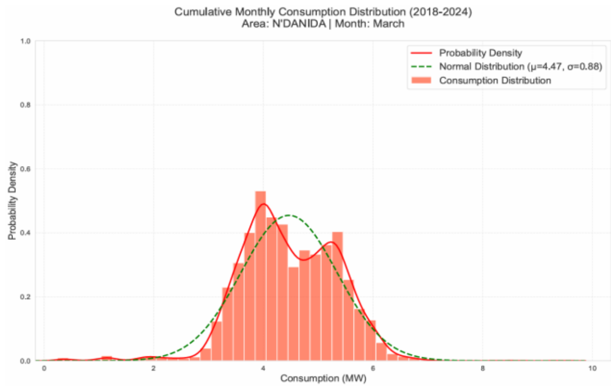

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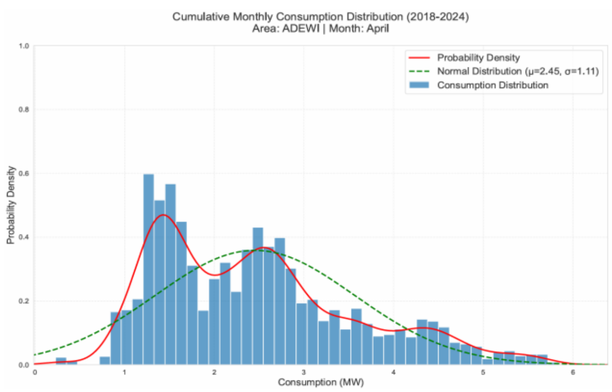
Fig. 5: Histograms of changes in consumption for the months of March for all sites from 2018 to 2024

Table 6 shows the statistical results of consumption at all sites for the months of April from 2018 to 2024.

Table 6: Statistical results for the months of April from 2018 to 2024

Paramètres statistiques										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5291	2.453	2.310	1.353	0.264	5.808	1.112	0.897	0.754	-0.103
ADIDOGOME	5291	3.623	3.960	0.132	0.099	8.250	1.695	1.243	-0.801	0.283
AVENOU	5291	4.872	4.455	3.960	0.924	9.306	1.415	1.208	0.229	-0.670
CASABLANCA	5291	3.349	3.360	3.360	0.330	6.798	1.015	0.741	0.357	0.193
DOGBEAVOU	5291	3.610	3.597	3.676	0.495	9.900	1.609	1.332	0.105	-0.781
GAKLI	5291	5.133	5.115	5.123	0.297	9.174	1.388	1.062	-0.156	1.093
GARAGE CENTRAL	5291	4.212	4.323	3.993	0.297	8.019	1.388	1.117	-0.092	-0.458
N'DANIDA	5291	4.347	4.356	4.620	0.594	7.557	0.911	0.741	-0.155	0.547

Figure 6 shows the evolution of consumption at each site for the months of April from 2018 to 2024.



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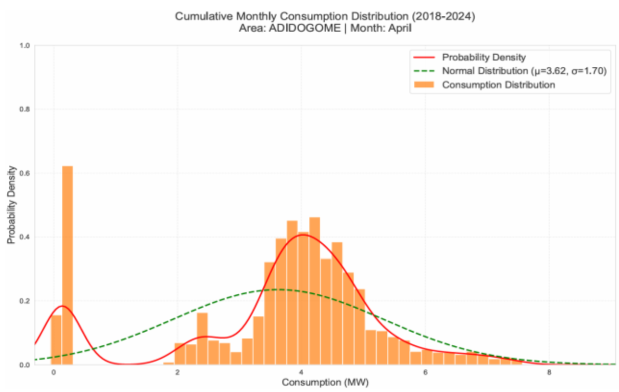

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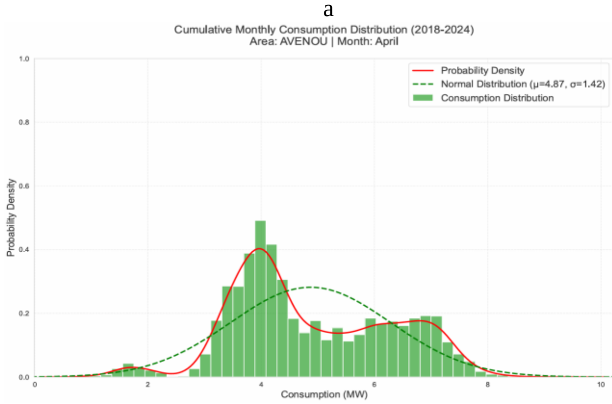

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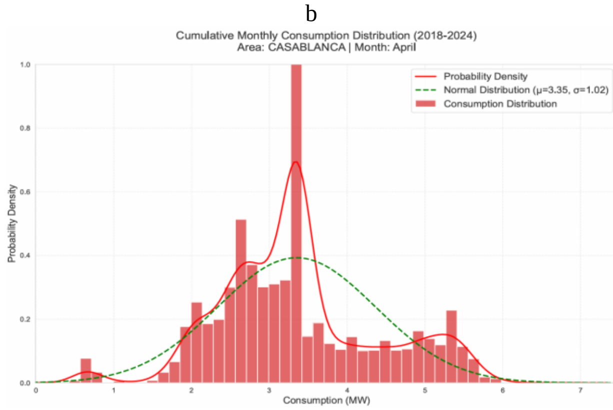

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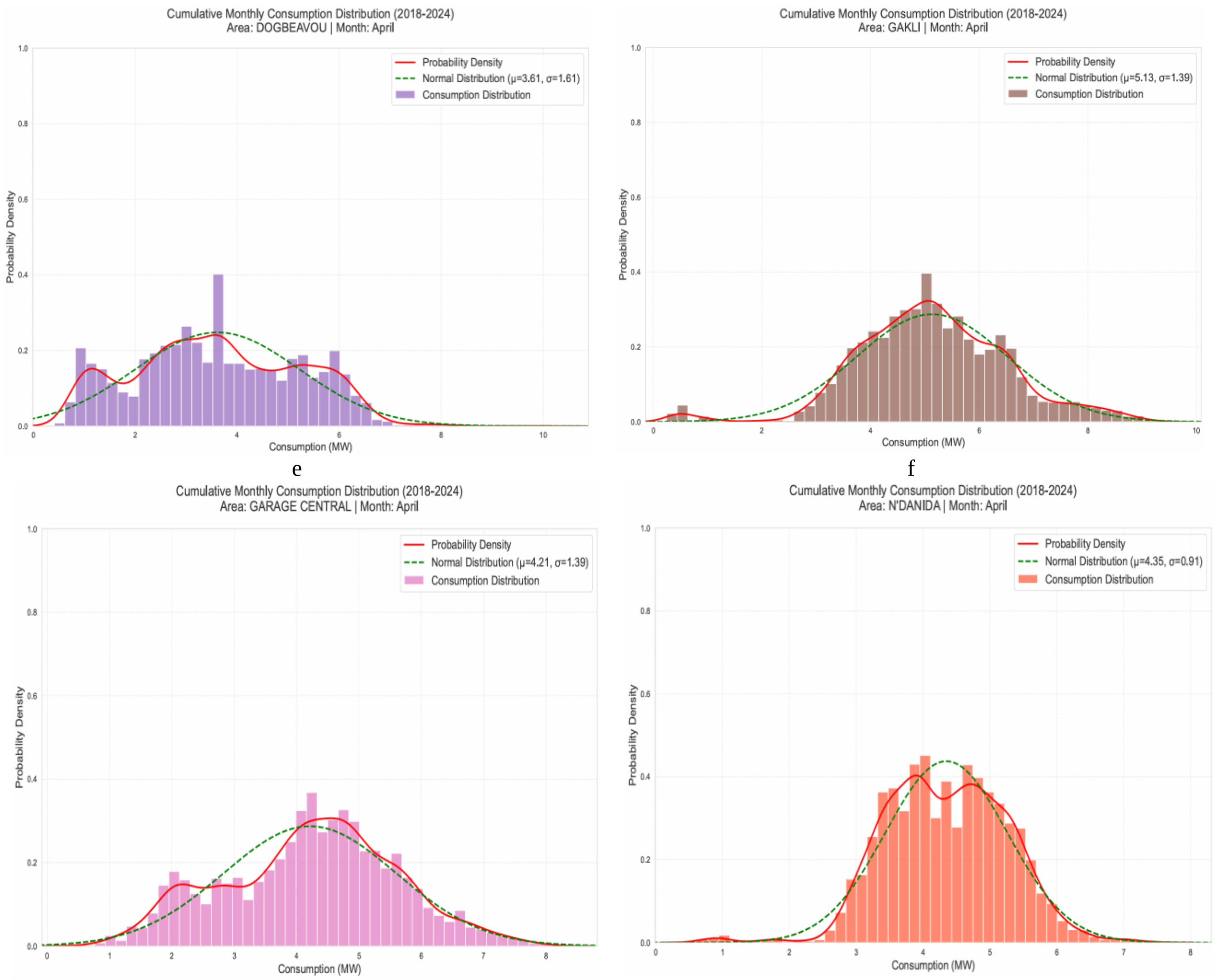

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Fig. 6: Graphs of changes in consumption for the month of April for all areas

The statistical results of electrical energy consumption for the months of May from 2018 to 2024 at the eight areas are presented in Table 7.

Table 7: Statistical results for the months of May from 2018 to 2024

Paramètres statistiques										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5368	2.550	2.409	2.574	0.561	5.643	1.028	0.809	0.729	-0.214
ADIDOGOME	5368	3.306	3.696	0.132	0.099	6.237	1.398	0.985	-1.428	0.992
AVENOU	5368	4.288	4.059	3.630	1.089	9.240	1.630	1.328	0.102	-0.711
CASABLANCA	5368	3.651	3.669	3.669	0.264	8.349	1.240	0.958	0.680	0.419
DOGBEAVOU	5368	3.574	3.366	3.300	0.198	9.900	1.615	1.305	0.437	-0.243
GAKLI	5368	4.983	4.983	5.346	0.495	9.801	1.259	0.998	0.104	0.296
GARAGE CENTRAL	5368	3.628	3.993	0.363	0.231	7.953	1.693	1.390	-0.487	-0.530
N'DANIDA	5368	4.162	4.224	3.630	0.264	7.062	1.017	0.786	-0.876	1.505

Figure 7 illustrates the evolution of electrical energy consumption at the eight sites for the month of May from 2018 to 2024.

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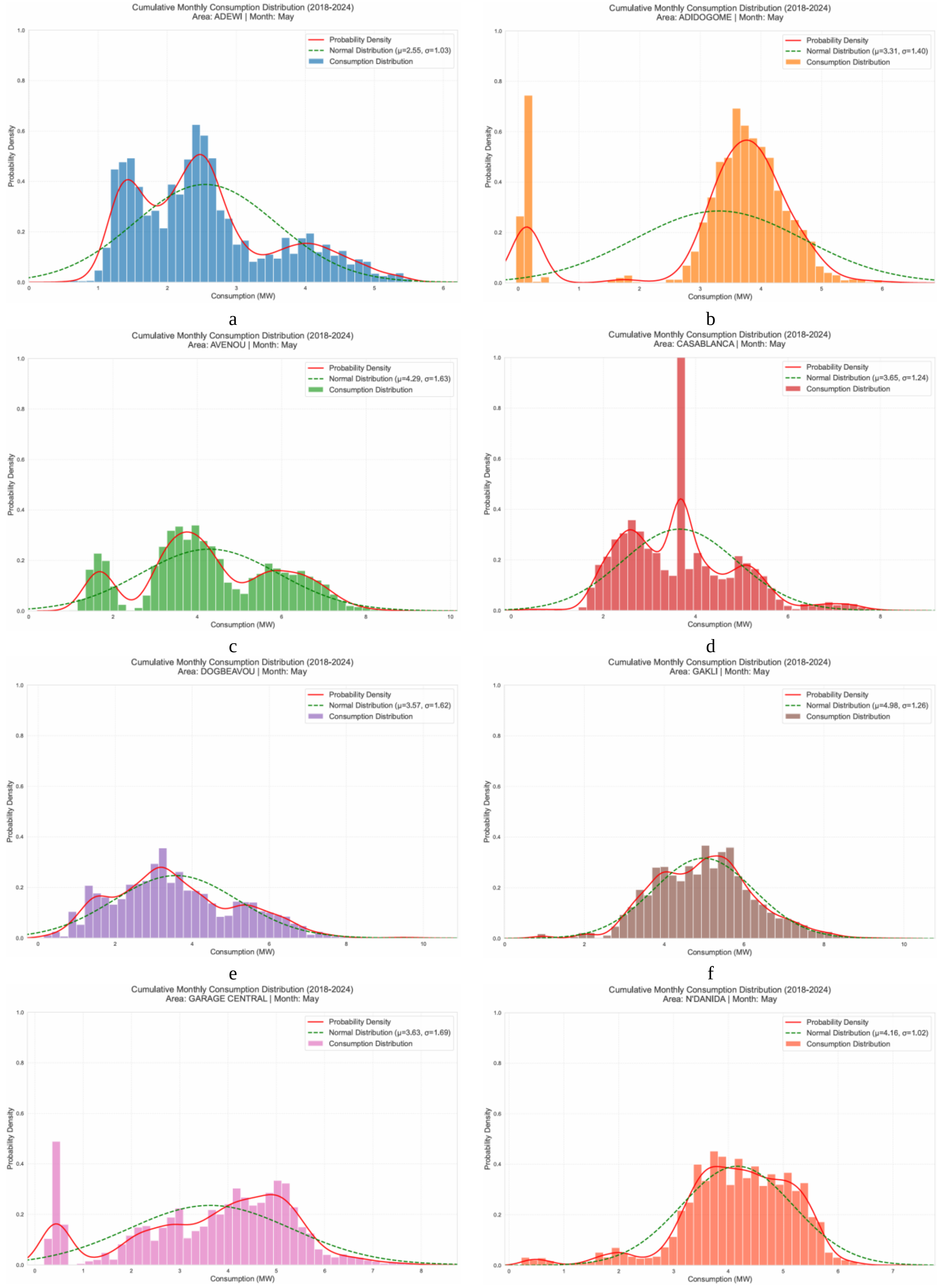


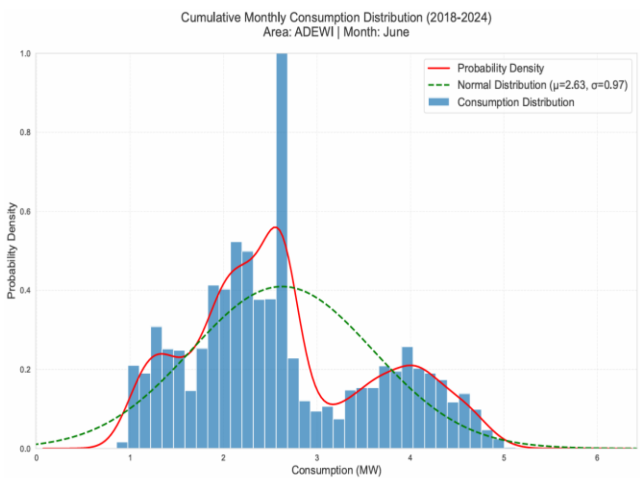
Fig. 7: Graphs showing changes in electricity consumption for the month of May for all sites from 2018 to 2024

Table 8 presents the statistical results of electricity consumption in each zone for the months of June from 2018 to 2024.

The histograms of changes in electricity consumption at each site for the months of June 2018 to 2024 are presented in Fig. 8.

Table 8: Statistical results for the months of June from 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5367	2.626	2.508	2.623	0.594	5.841	0.973	0.770	0.478	-0.606
ADIDOGOME	5367	2.668	3.333	2.676	0.099	7.491	1.498	1.255	-0.793	-0.818
AVENOU	5367	4.154	3.927	3.135	1.188	8.580	1.580	1.351	0.013	-0.922
CASABLANCA	5367	2.834	2.834	2.834	0.297	5.643	0.857	0.646	0.637	0.289
DOGBEAVOU	5367	3.245	3.257	2.541	0.132	7.656	1.348	1.102	0.046	-0.394
GAKLI	5367	4.388	4.422	3.762	0.297	8.910	1.170	0.918	-0.044	0.971
GARAGE CENTRAL	5367	3.127	3.300	0.330	0.264	7.557	1.494	1.221	-0.283	-0.409
N'DANIDA	5367	3.735	3.861	4.389	0.165	8.547	1.060	0.856	-0.407	-0.220



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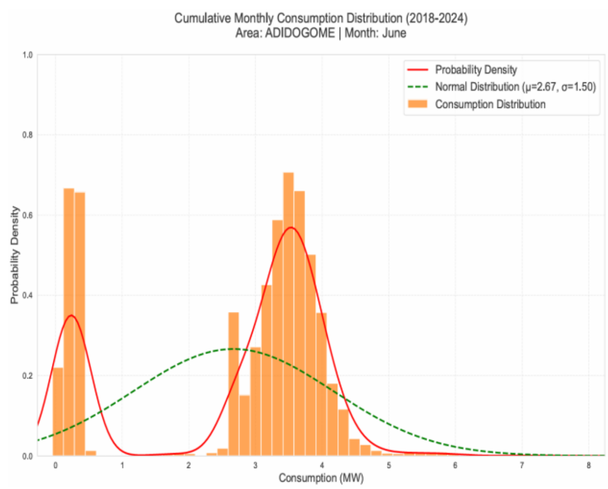

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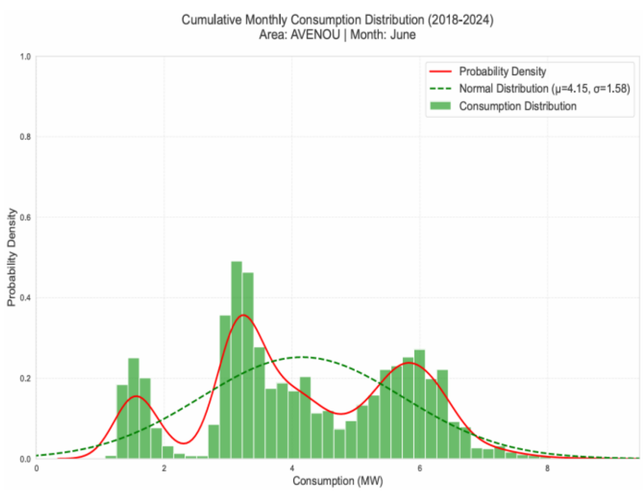

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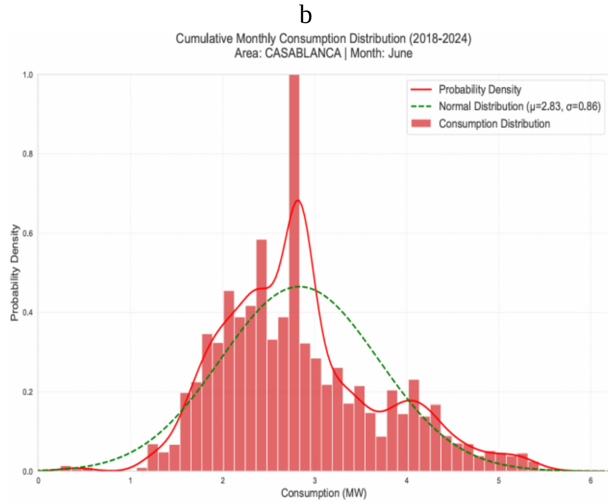

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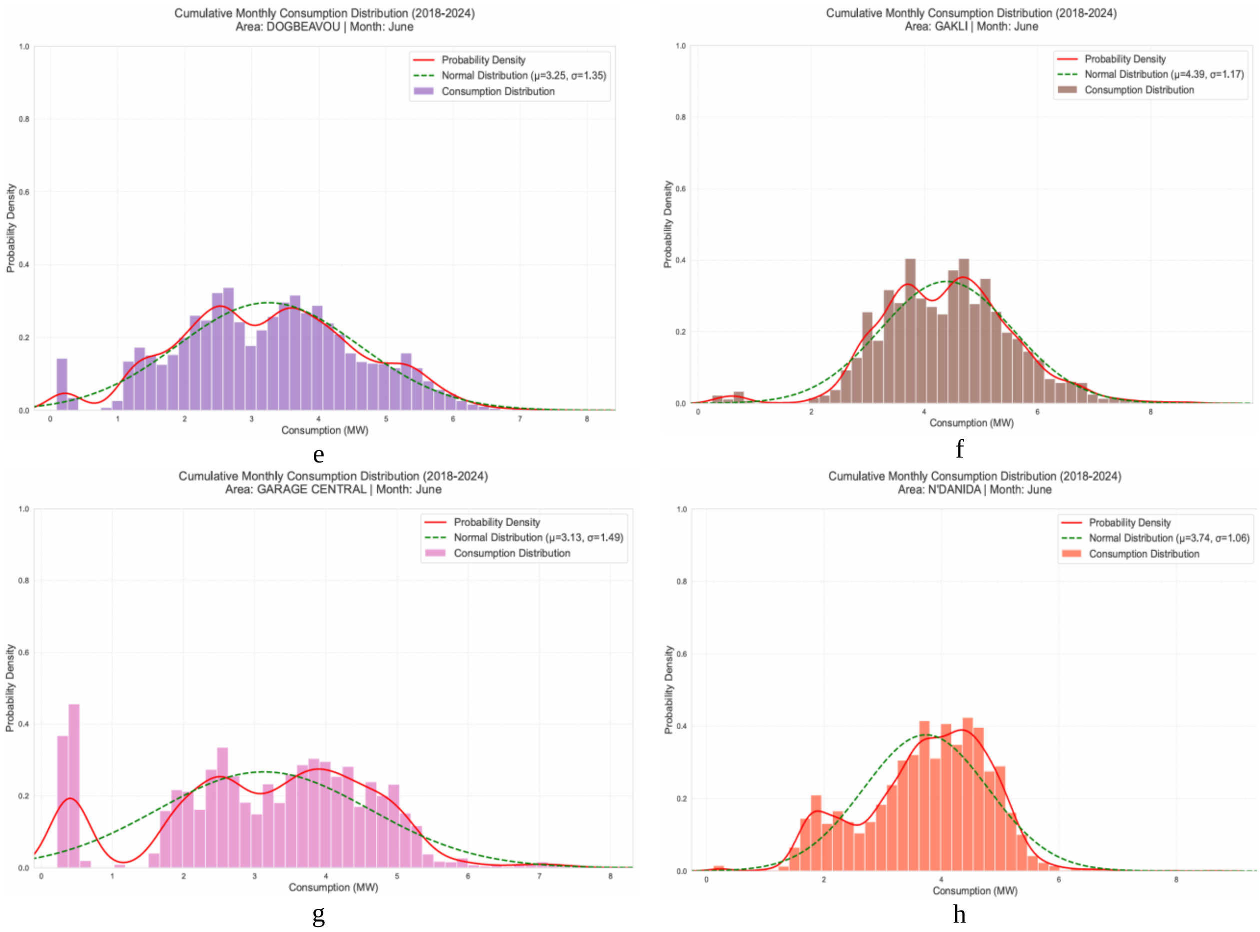

Fig. 8: Graphs showing changes in electricity consumption for the months of June for all areas from 2018 to 2024.

Table 9 shows the statistical results of electricity consumption for the months of July 2018 to 2024 for all areas.

Table 9: Statistical results for the months of July from 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5445	2.575	2.588	2.588	0.528	7.029	0.888	0.722	0.209	-0.703
ADIDOGOME	5445	2.653	3.300	0.099	0,099	7.557	1.613	1.348	-0.433	-0.636
AVENOU	5445	4.062	3.993	4.056	0.462	8.976	1.476	1.194	-0.185	-0.655
CASABLANCA	5445	2.841	2.640	2.866	0.693	6.798	1.082	0.756	1.560	2.361
DOGBEAVOU	5420	3.089	3.003	3.300	0.330	7.128	1.124	0.930	0.406	-0.401
GAKLI	5445	3.925	3.894	3.663	0.198	7.095	1.150	0.892	-0.712	1.287
GARAGE CENTRAL	5445	3.080	3.267	2.310	0.264	6.204	1.304	1.099	-0.370	-0.547
N'DANIDA	5445	3.576	3.729	3.828	0.231	7.600	0.995	0.765	-0.515	0.803

Figure 9 illustrates the distribution of electricity consumption across the eight for the months of July from 2018 to 2024.

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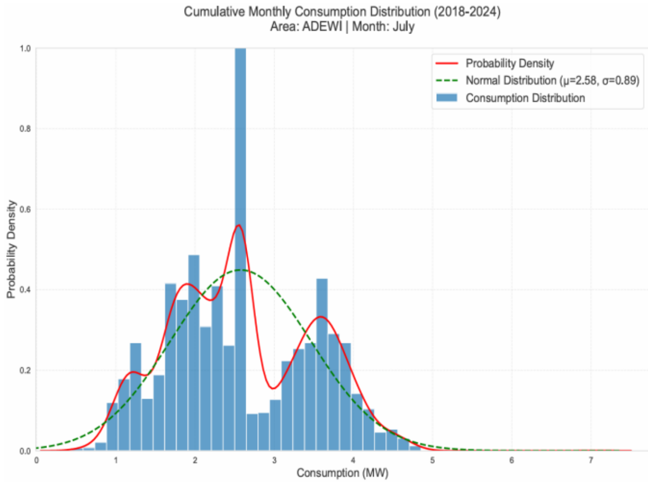

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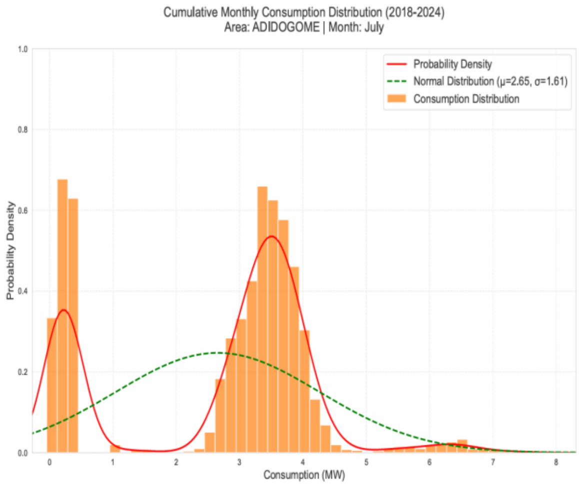

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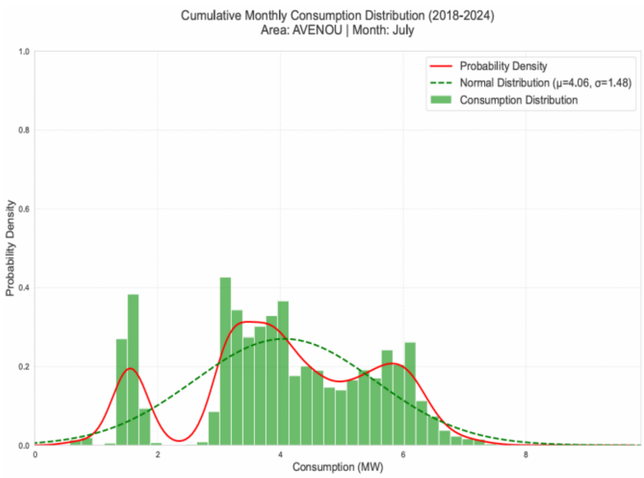

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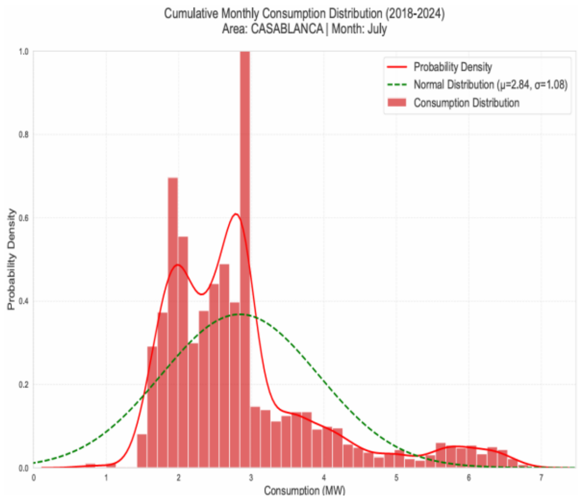

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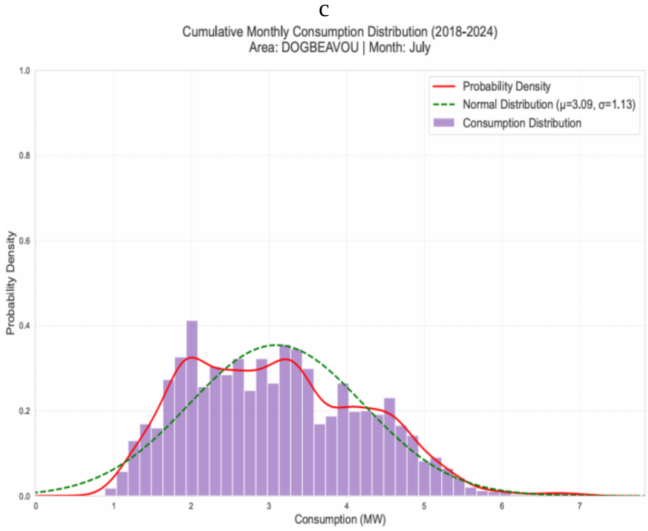

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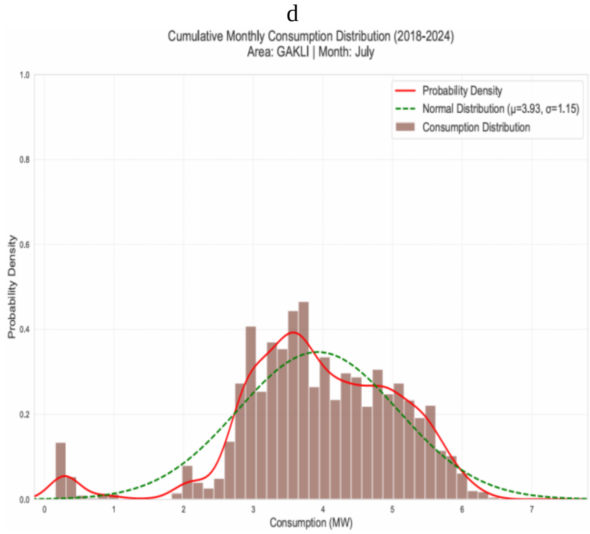

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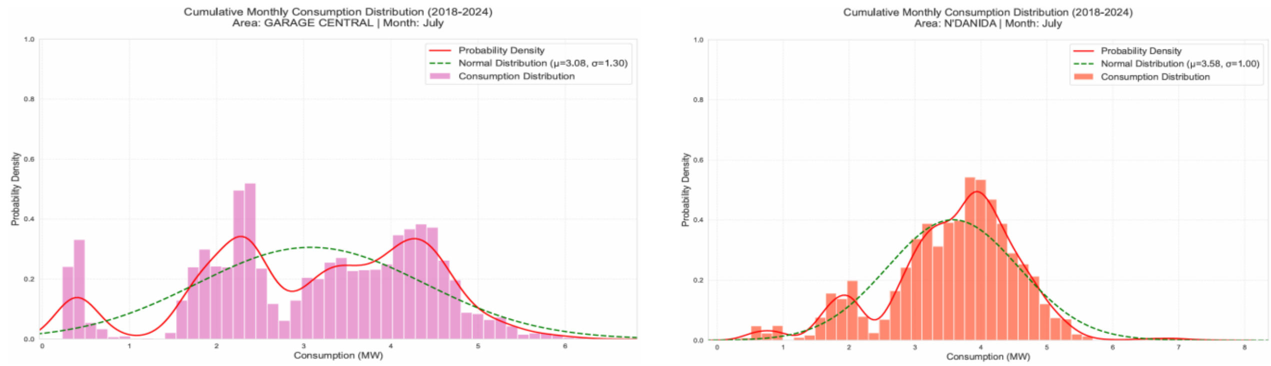

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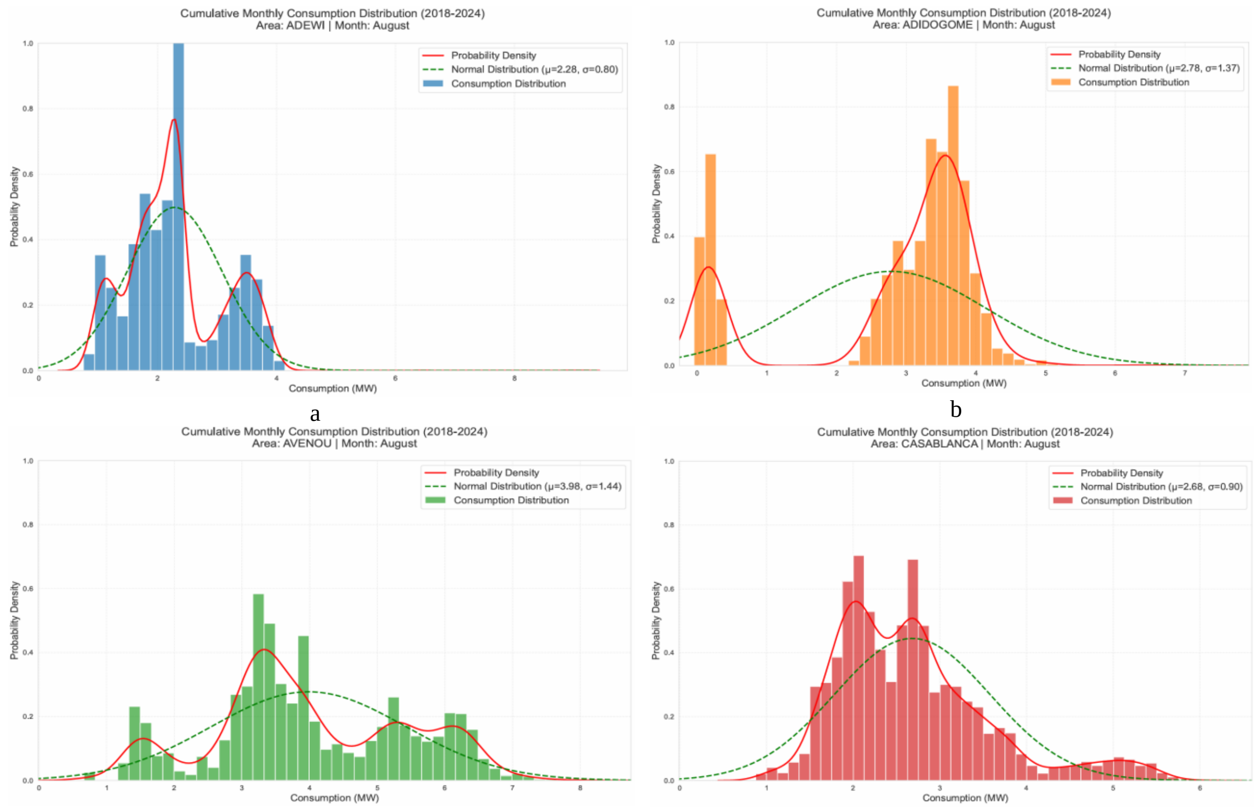
Fig. 9: Graphs showing changes in electricity consumption for the month of July for all areas from 2018 to 2024

The statistical results of electricity consumption per site for the months of August 2018 to 2024 are presented in Table 10.

Table 10: Statistical results by site for the months of August 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5323	2.2849	2.244	2.320	0.759	9.000	0.800	0.621	0.500	0.296
ADIDOGOME	5323	2.7778	3.333	0.099	0.099	7.194	1.370	1.069	-1.141	-0.106
AVENOU	5323	3.9849	3.729	3.300	0.627	7.953	1.439	1.180	0.117	-0.678
CASABLANCA	5323	2.6806	2.541	2.046	0.924	6.000	0.897	0.681	1.101	1.163
DOGBEAVOU	5323	2.8651	2.805	1.914	0.231	9.600	1.127	0.961	0.295	-0.296
GAKLI	5323	3.8772	3.993	3.234	0.264	7.623	1.049	0.813	-0.592	1.377
GARAGE CENTRAL	5323	3.3475	3.333	2.277	0.264	9.306	1.244	1.044	0.345	-0.575
N'DANIDA	5323	3.5004	3.564	3.960	0.363	6.501	0.992	0.794	-0.209	-0.343

Figure 10 shows the evolution of electricity consumption per site for the months of August from 2018 to 2024.



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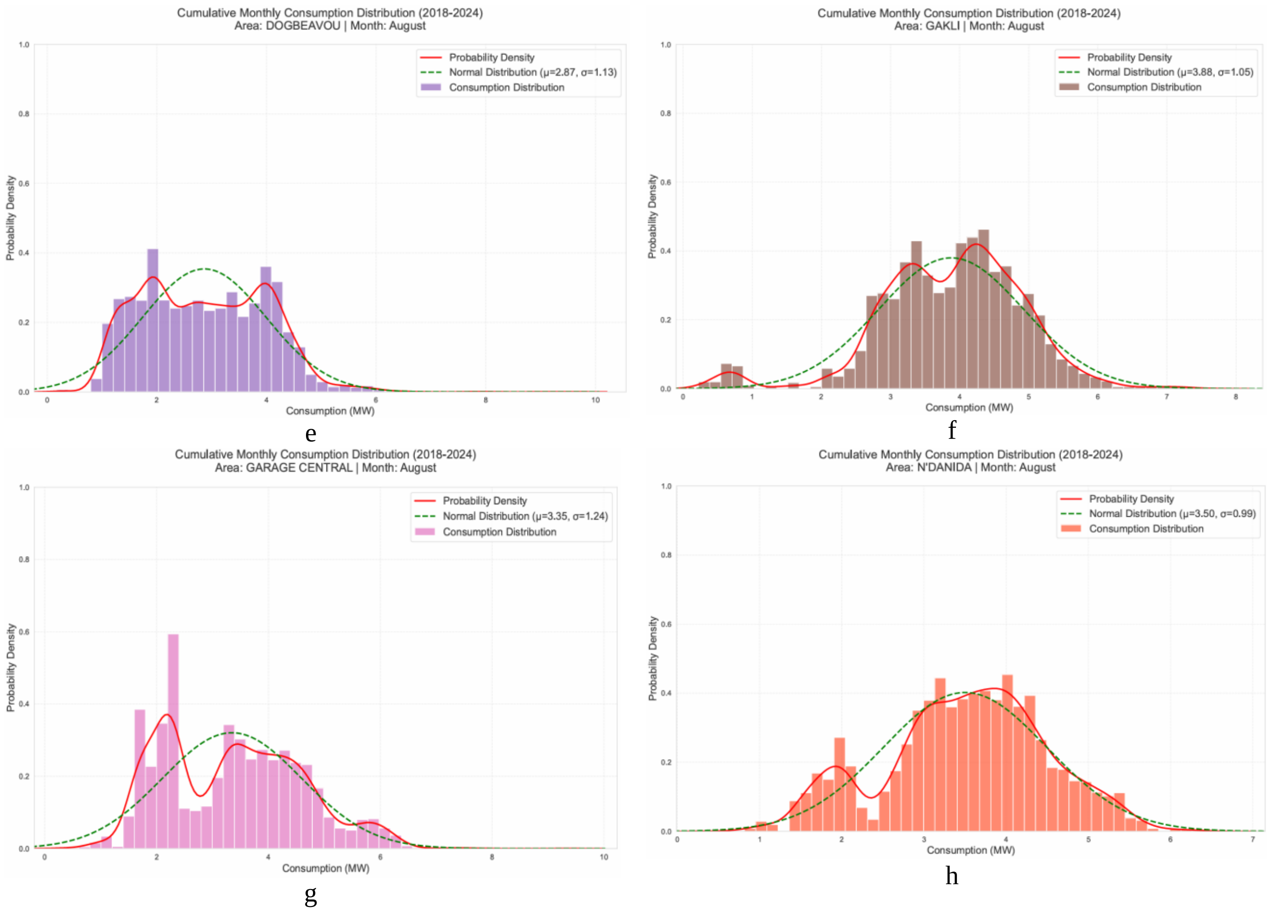

Fig. 10: Graphs showing changes in electricity consumption for the month of August at each area

Table 11 presents statistical results of electrical energy consumption from September 2018 to 2024 at all areas.

Table 11: Statistical results for the months of September from 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5222	2.672	2.277	2.013	0.891	6.996	1.230	0.990	1.067	0.835
ADIDOGOME	5222	2.826	3.069	2.807	0.099	8.052	1.259	0.854	-0.985	1.206
AVENOU	5222	4.310	3.828	3.300	1.056	9.207	1.384	1.227	0.491	-0.901
CASABLANCA	5222	3.074	3.087	2.277	0.264	6.732	1.028	0.868	-0.037	-0.504
DOGBEAVOU	5197	2.874	2.508	2.310	0.858	6.699	1.170	1.018	0.473	-0.885
GAKLI	5222	3.827	3.861	3.816	0.231	7.887	1.121	0.837	-0.451	1.054
GARAGE CENTRAL	5222	3.472	3.503	3.503	0.264	8.019	1.079	0.857	-0.045	0.288
N'DANIDA	5222	3.636	3.663	4.290	0.462	7.029	1.021	0.817	-0.140	-0.119

Figure 11 illustrates the evolution of electricity consumption at all areas from September 2018 to 2024.

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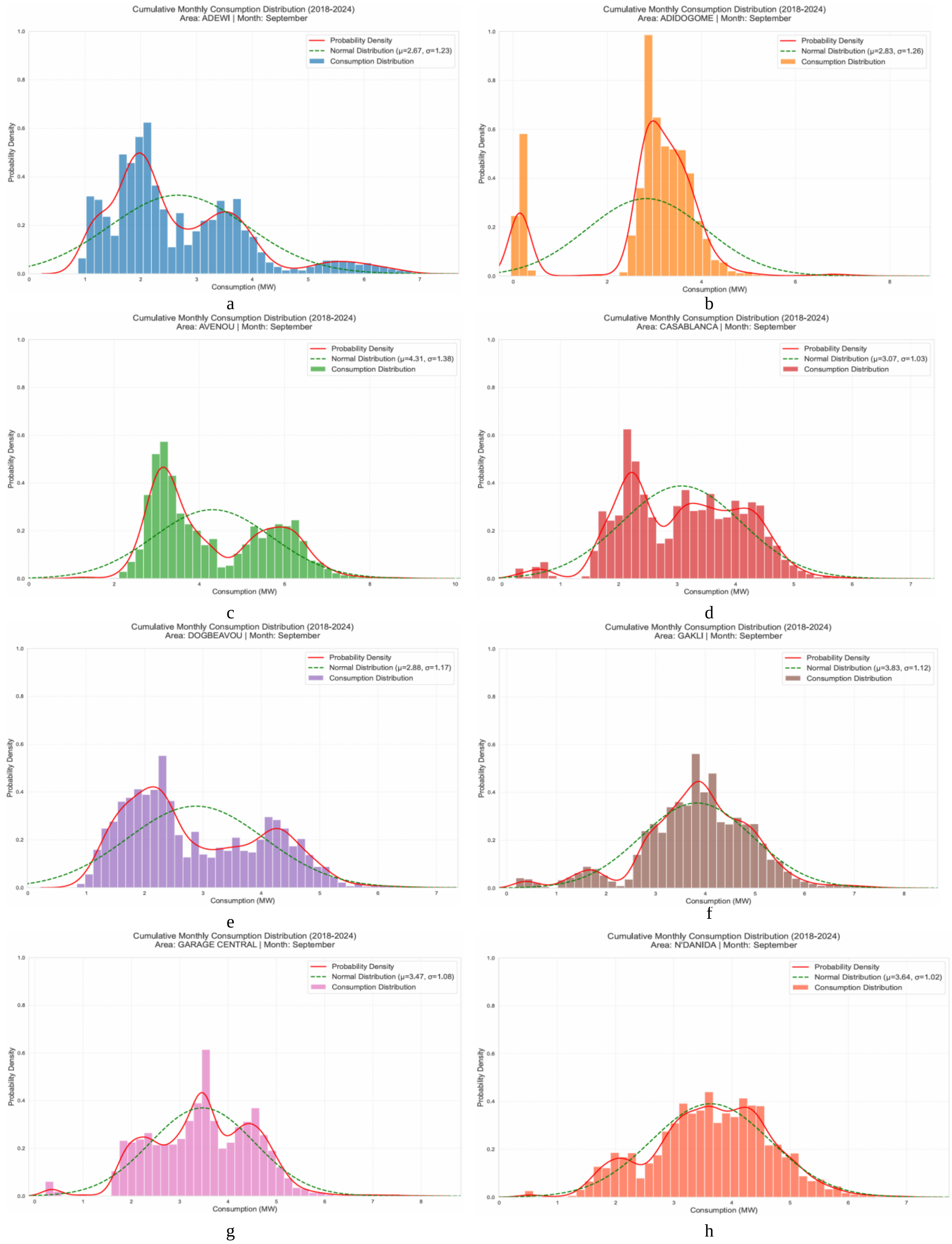

Fig. 11: Graphs showing changes in electricity consumption for the months of September for all areas from 2018 to 2024

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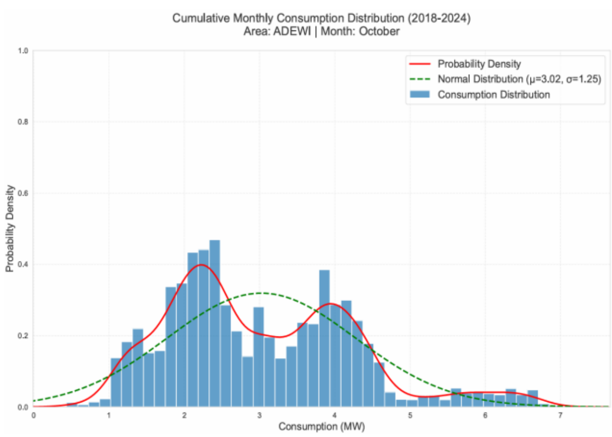
Table 12 presents the statistical results of electricity consumption of the eight sites for the months of October from 2018 to 2024.

Table 12: Statistical results for the months of October from 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5474	3.023	2.739	3.024	0.495	6.963	1.250	1.034	0.663	0.090
ADIDOGOME	5474	2.588	2.904	2.611	0.099	7.887	1.534	1.169	-0.179	-0.072
AVENOU	5474	4.748	4.760	4.760	0.099	9.933	1.494	1.273	0.155	-0.246
CASABLANCA	5474	3.173	3.182	3.182	0.330	6.864	0.925	0.765	0.141	-0.061
DOGBEAVOU	5474	3.551	3.577	3.577	0.132	8.613	1.423	1.188	-0.224	-0.287
GAKLI	5474	4.223	4.244	4.244	0.264	9.570	1.596	1.213	0.081	0.019
GARAGE CENTRAL	5474	3.652	3.729	3.645	0.066	8.514	1.186	0.943	-0.202	0.265
N'DANIDA	5474	3.821	3.828	3.564	0.231	9.537	1.066	0.779	-0.014	1.969

Figure 12 illustrates the histograms of changes in electricity consumption at the eight sites for the months of October from 2018 to 2024.



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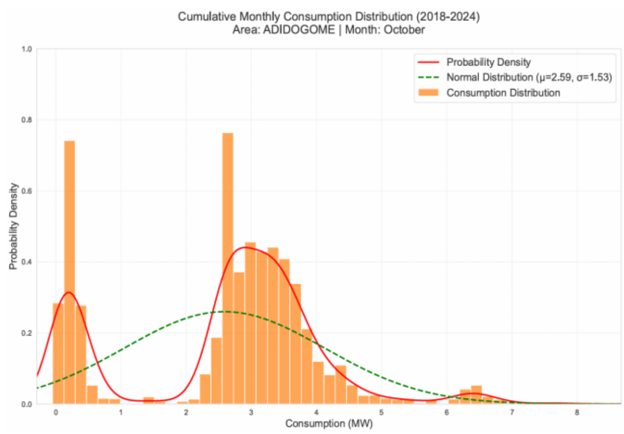

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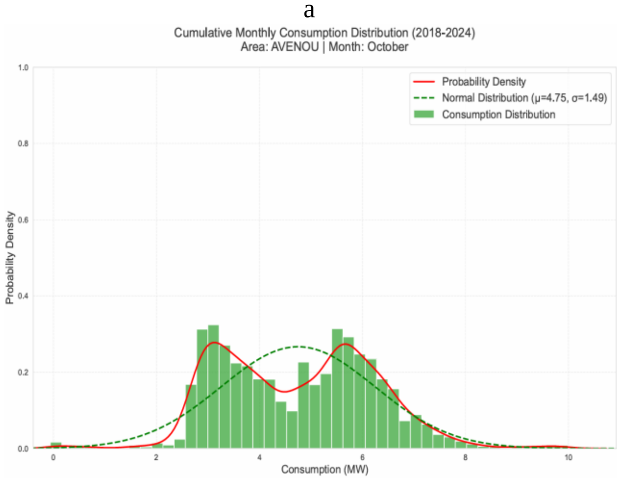

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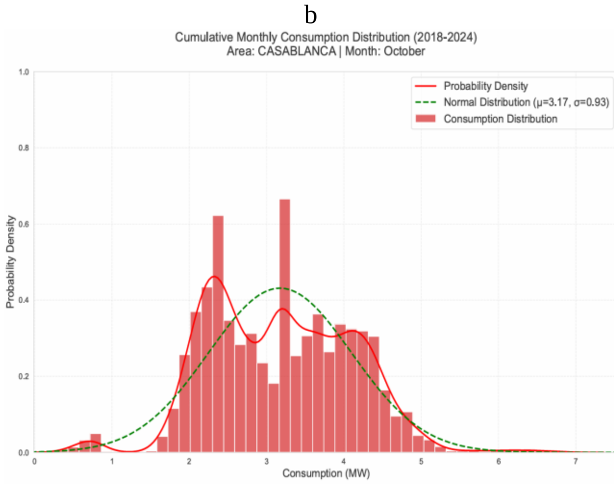

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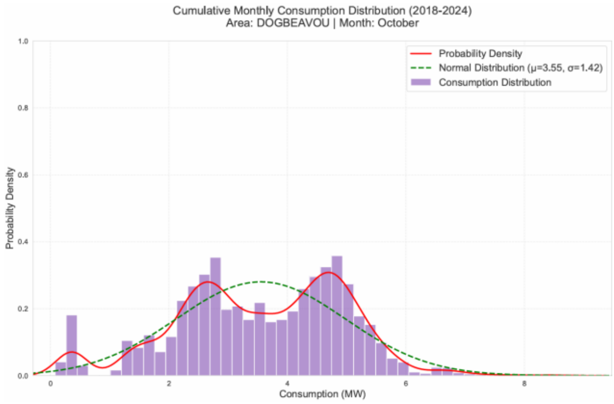

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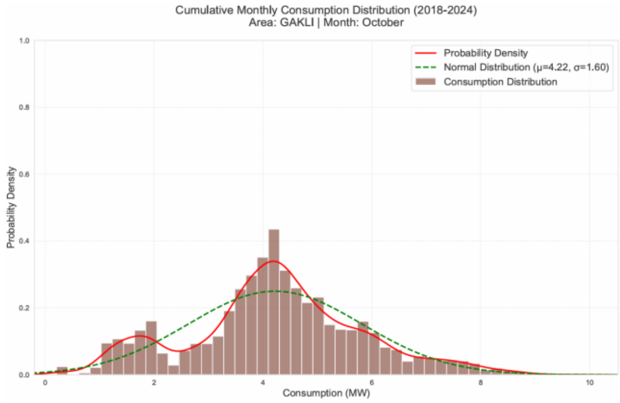

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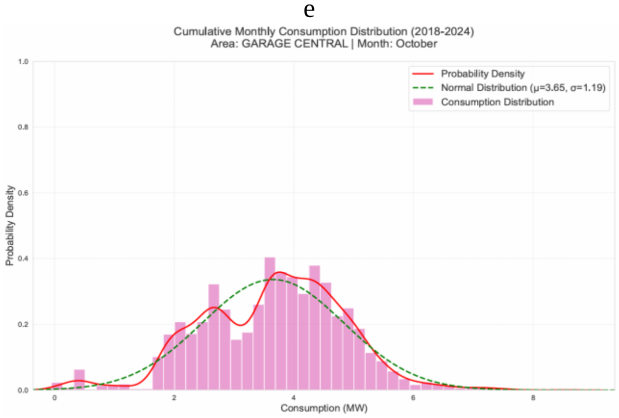

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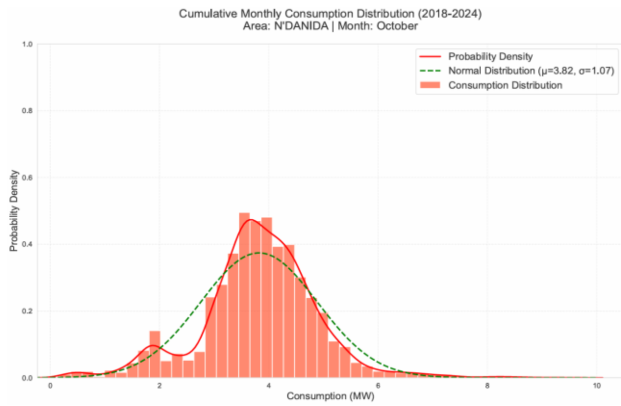

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Fig. 12: Graphs showing changes in electricity consumption for the month of October at the eight areas

Table 13 shows the statistical results of electricity consumption for the months of November at all sites from 2018 to 2024.

Table 13: Statistical results for the months of November from 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5238	3.060	2.706	2.376	0.429	8.349	1.427	1.175	0.749	0.425
ADIDOGOME	5238	2.903	3.300	0.132	0.099	9.438	1.632	1.231	-0.418	0.148
AVENOU	5238	4.491	4.125	3.300	0.891	9.999	1.743	1.494	0.204	-0.683
CASABLANCA	5238	3.208	3.212	3.212	0.495	6.270	1.018	0.797	0.303	-0.261
DOGBEAVOU	5238	3.494	3.234	0.231	0.132	8.910	1.863	1.490	0.149	-0.426
GAKLI	5238	4.650	4.719	4.719	0.297	9.735	1.515	1.144	-0.156	0.534
GARAGE CENTRAL	5238	4.082	4.092	4.083	0.528	9.240	1.259	0.993	0.090	0.185
N'DANIDA	5238	4.224	4.257	4.444	0.297	8.448	1.003	0.736	-0.287	2.361

Figure13 illustrates the evolution of electricity consumption at all sites for the months of November from 2018 to 2024.

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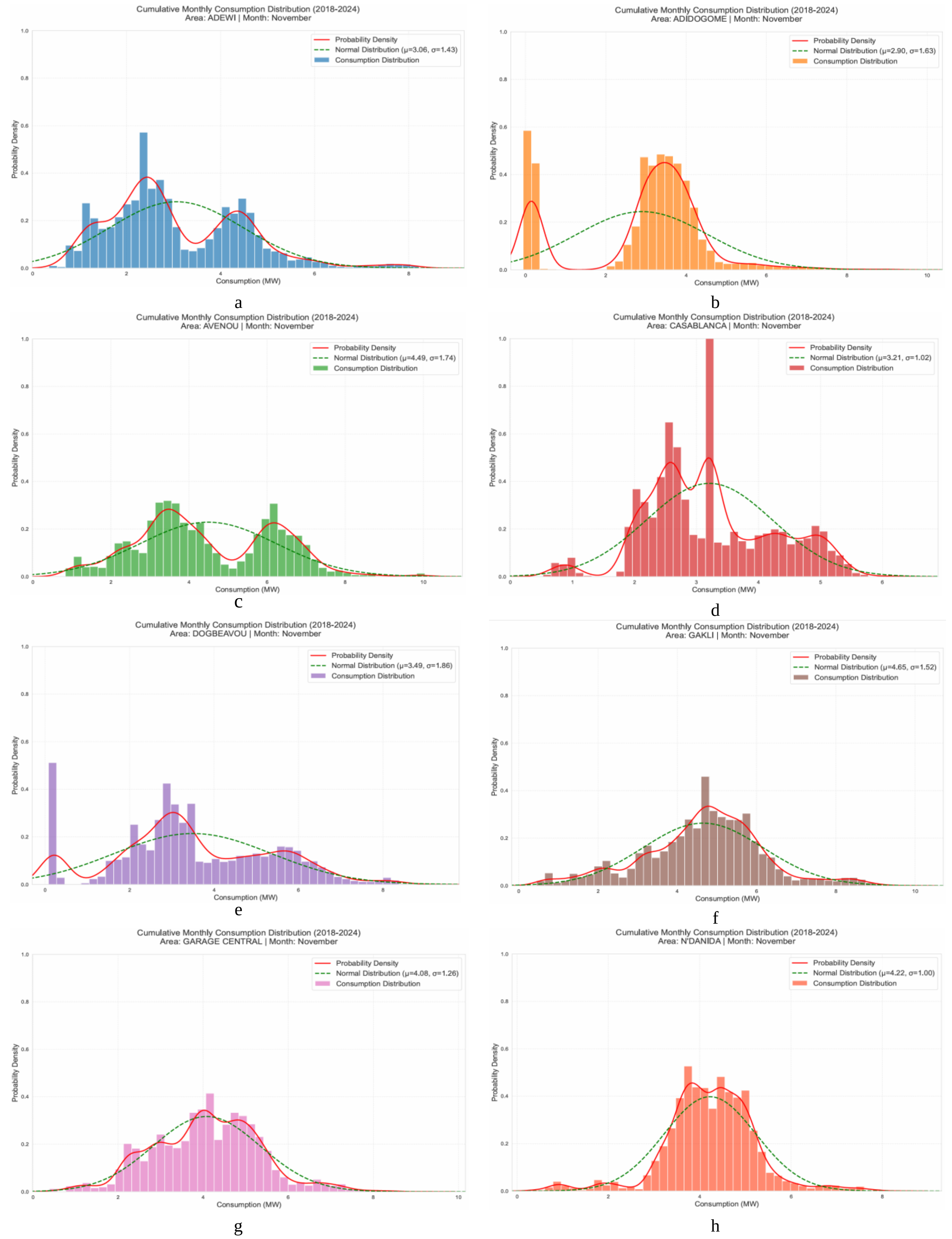

Fig. 13: Graphs of changes in electricity consumption at each area for the months of November 2018 to 2024

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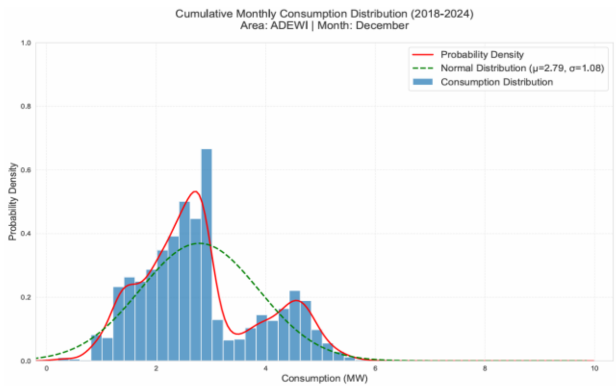
Table 14 presents the statistical results of electricity consumption per site for the months of December 2018 to 2024

Table 14: Statistical results for the months of December from 2018 to 2024

Statistical parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	5332	2.789	2.640	2.833	0.264	9.400	1.080	0.840	0.562	-0.208
ADIDOGOME	5332	3.475	3.762	3.437	0.099	9.207	1.565	1.094	-0.928	0.878
AVENOU	5332	4.666	4.323	4.735	1.287	9.636	1.420	1.154	0.566	-0.231
CASABLANCA	5332	3.399	3.267	3.396	0.396	7.689	1.072	0.868	0.278	-0.332
DOGBEAVOU	5332	3.473	3.399	3.472	0.330	7.920	1.565	1.285	0.152	-0.579
GAKLI	5332	4.559	4.653	4.552	0.363	9.075	1.392	1.057	-0.554	0.431
GARAGE CENTRAL	5332	3.934	3.923	3.923	0.231	8.712	1.277	1.006	-0.042	-0.114
N'DANIDA	5332	4.404	4.389	4.397	0.264	8.052	0.824	0.648	-0.291	2.811

Figure14 shows the evolution of electricity consumption at each site for the months of December 2018 to 2024.



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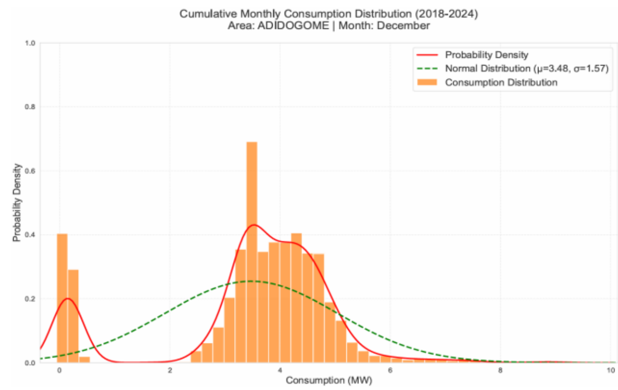

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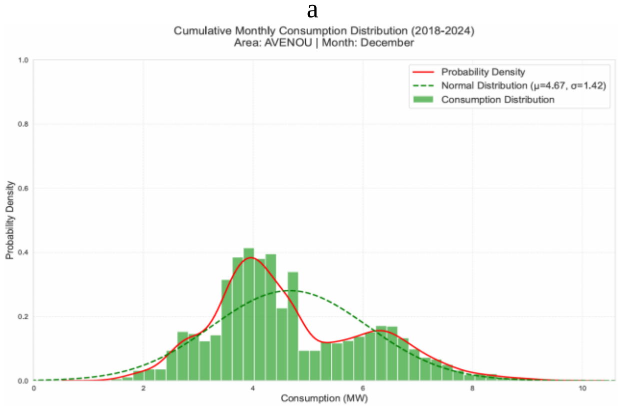

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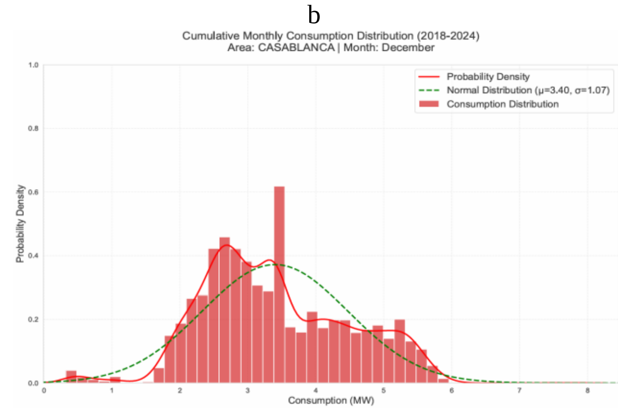

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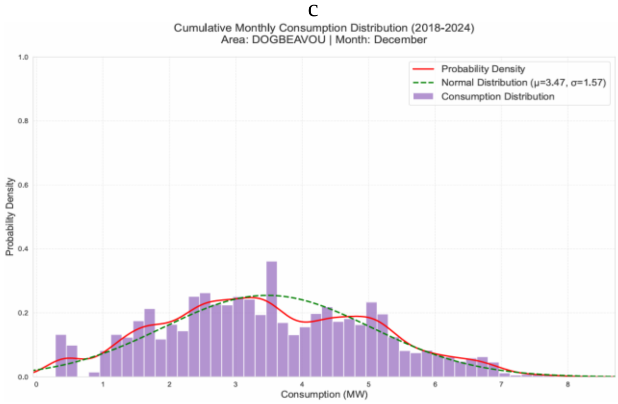

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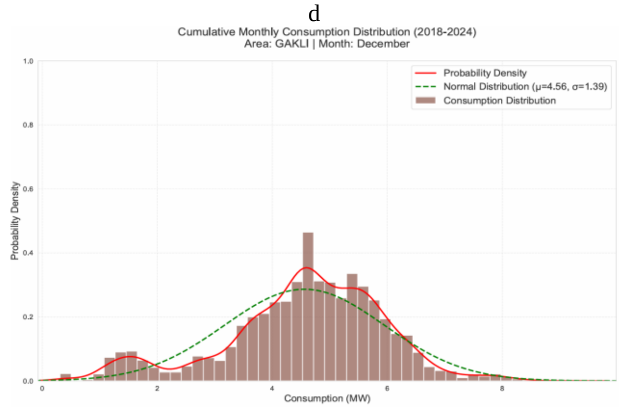

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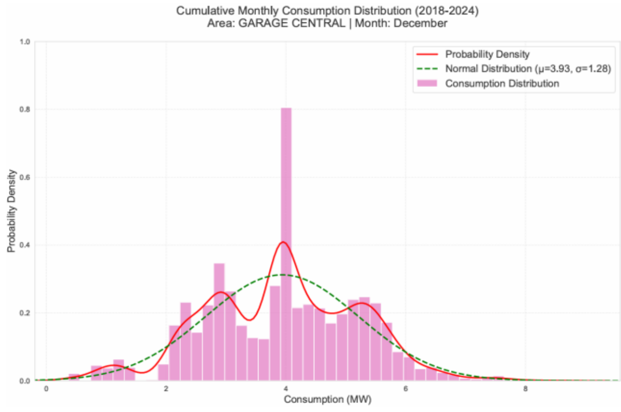

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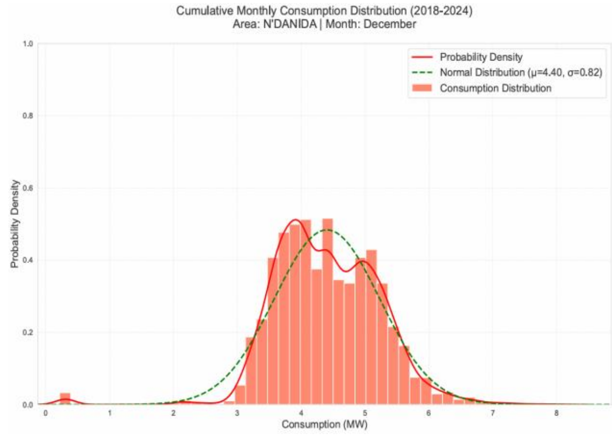

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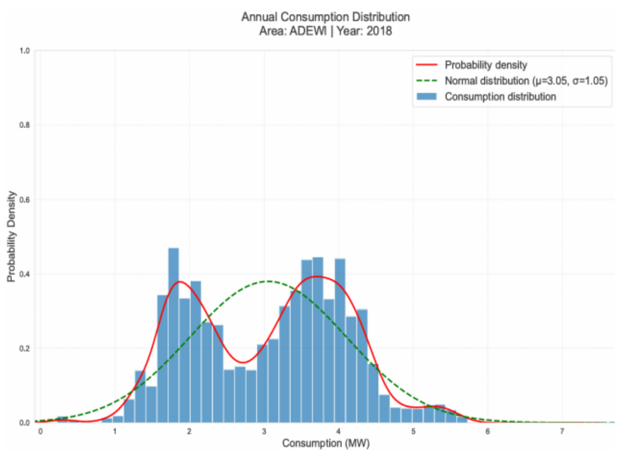
Fig. 14: Graphs showing changes in electricity consumption for the months of December for all areas from 2018 to 2024

Table 15 presents the statistical results of electricity consumption at each area for the year 2018.

Table 15: Statistical results by area for the year 2018

Statistical parameters											
year	Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
2018	ADEWI	8999	3.054	3.234	1.815	0.264	7.029	1.050	0.911	0.008	-0.865
2018	ADIDOGOME	8999	3.549	3.465	3.432	0.363	9.207	0.804	0.545	1.628	6.291
2018	AVENOU	8999	6.256	6.204	6.270	0.528	9.999	0.832	0.537	-1.351	12.856
2018	CASABLANCA	8999	2.237	2.145	1.914	0.264	6.072	0.611	0.410	2.053	8.339
2018	DOGBEAVOU	8249	4.435	4.455	4.983	0.396	7.425	1.212	1.005	-0.139	-0.504
2018	GAKLI	8999	4.100	3.960	3.300	0.726	8.217	1.035	0.861	0.380	0.018
2018	GARAGE CENTRAL	8999	4.580	4.521	4.290	0.495	9.306	0.842	0.660	0.461	1.139
2018	N'DANIDA	8999	4.932	4.917	4.950	0.264	8.448	0.633	0.444	-0.587	9.133

Figure 15 shows the distribution of electricity consumption across the eight sites during 2018.



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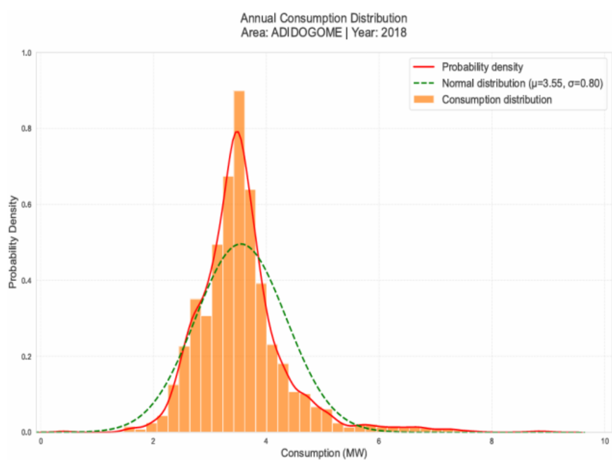

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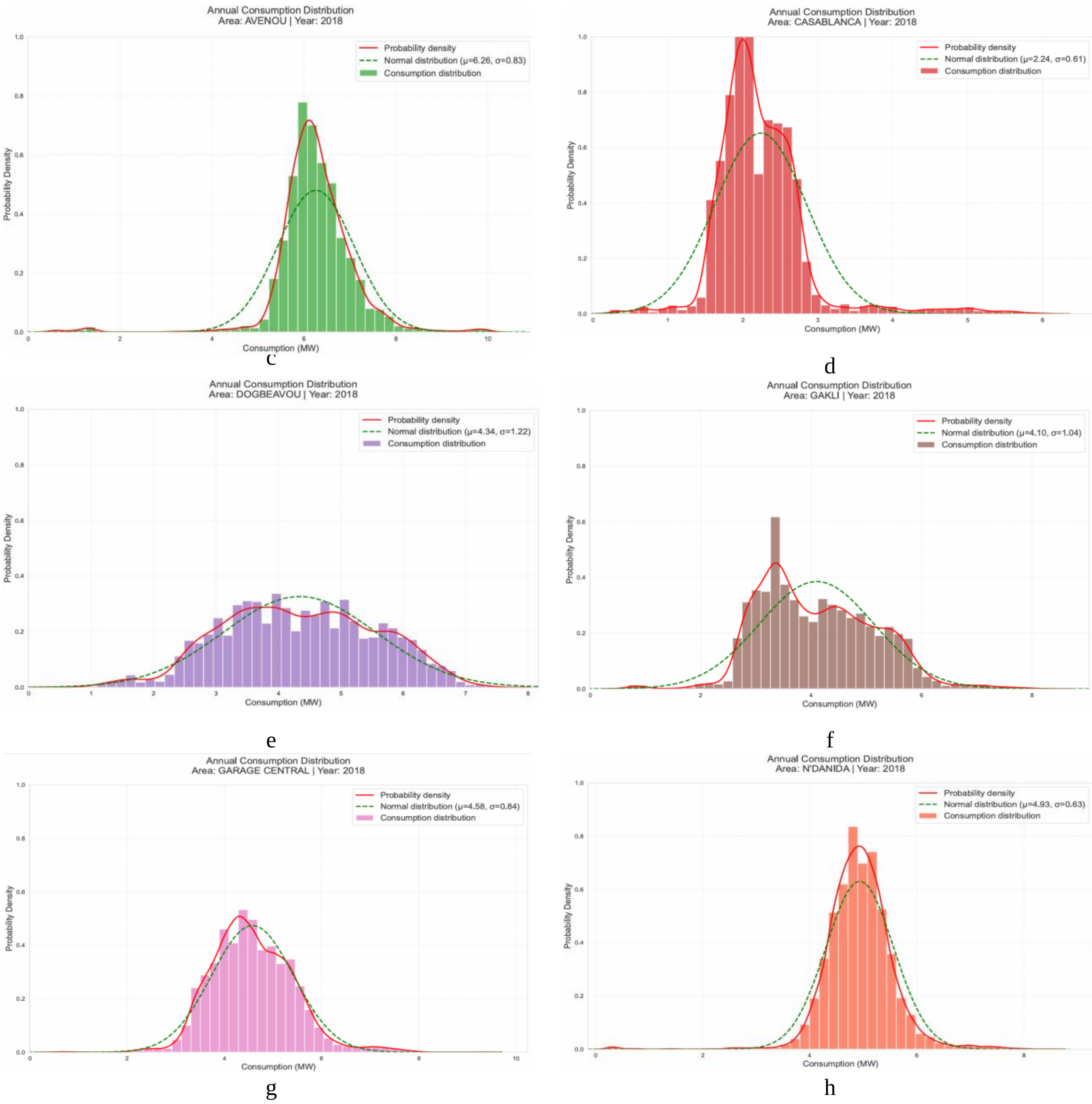

Fig. 15: Histograms of changes in electricity consumption during 2018 for all areas

Table 16 presents the statistical results of electricity consumption at each site during the year 2019.

Table 16: Statistical results by site for the year 2019

Statistical parameters											
Year	Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
2019	ADEWI	9228	3.049	2.623	2.320	0.264	6.996	1.300	1.032	0.662	0.133
2019	ADIDOGOME	9228	4.051	3.960	3.795	0.264	8.976	0.809	0.616	0.295	2.510
2019	AVENOU	9228	4.319	3.828	3.828	0.264	9.966	1.412	1.170	0.731	-0.149
2019	CASABLANCA	9228	3.516	3.360	3.669	0.264	7.689	0.884	0.725	0.480	-0.210
2019	DOGBEAVOU	8454	4.508	4.455	4.290	0.330	8.910	1.253	1.031	0.170	-0.292
2019	GAKLI	9228	4.974	4.917	4.785	0.264	9.570	0.940	0.707	-0.726	3.651
2019	GARAGE CENTRAL	9228	4.638	4.554	3.923	0.330	9.240	0.895	0.709	0.178	1.289
2019	N'DANIDA	9228	4.730	4.620	4.290	1.122	8.415	0.762	0.605	0.353	0.957

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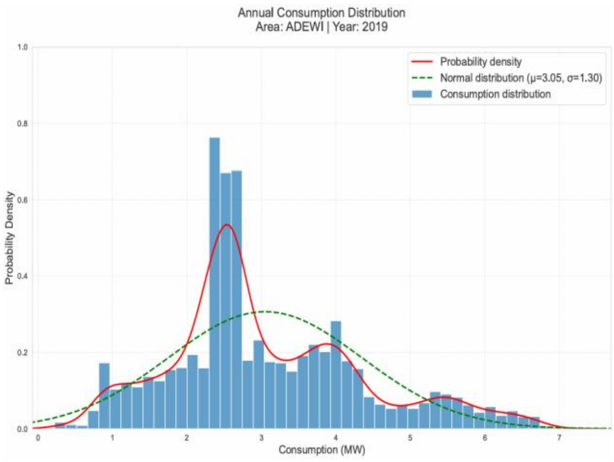
Figure16 illustrates the evolution of electricity consumption at each site during 2019.



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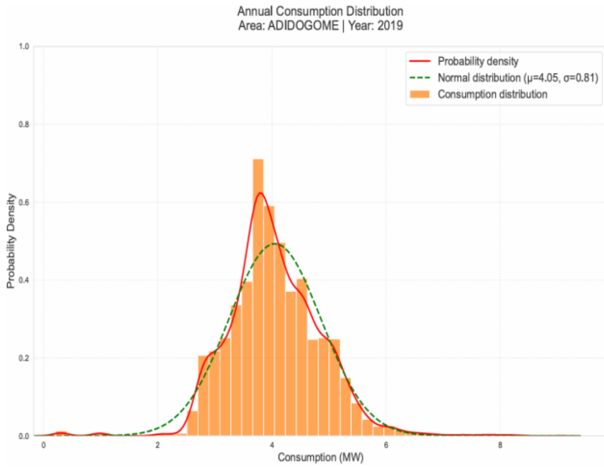

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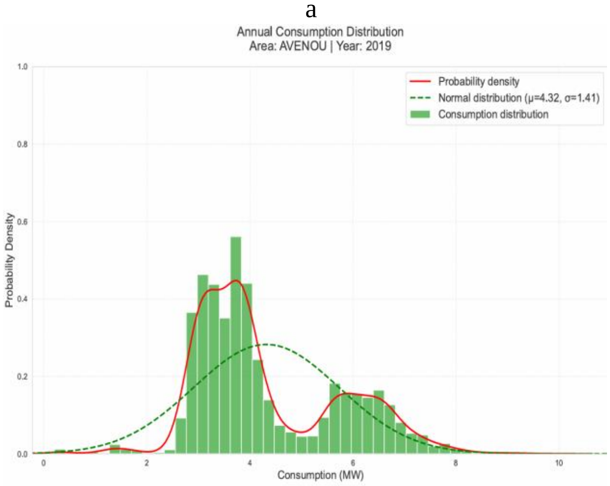

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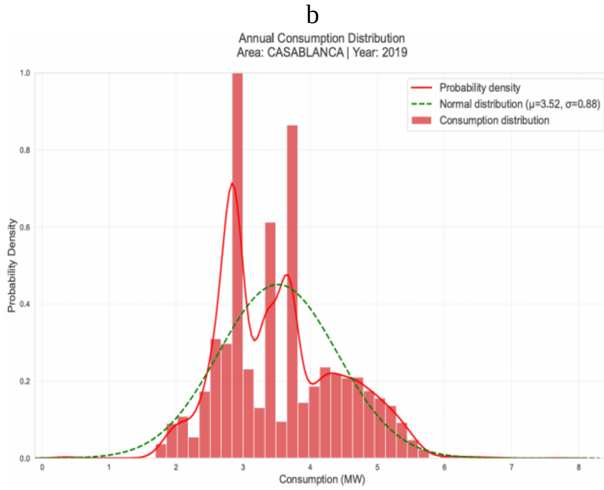

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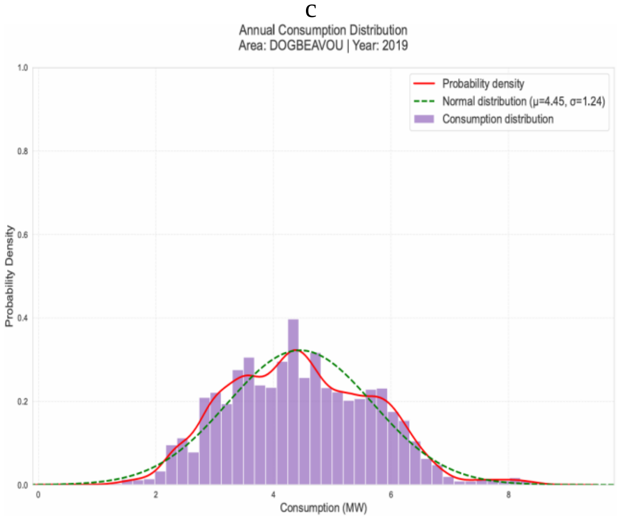

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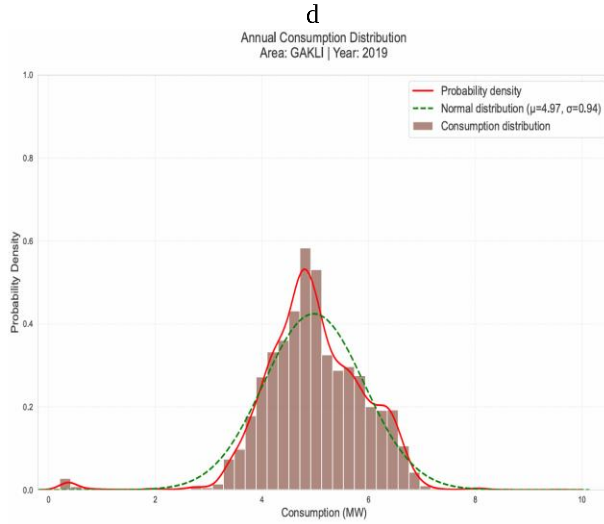

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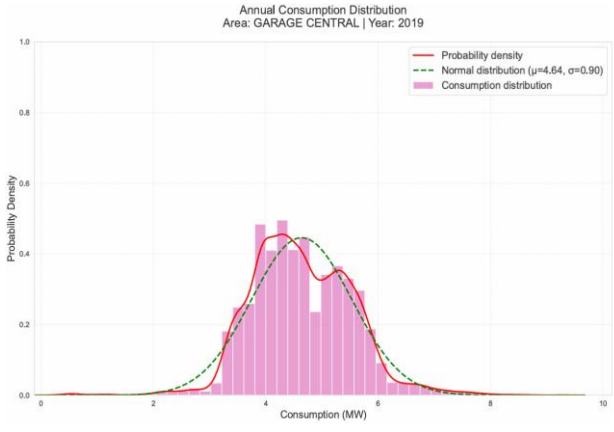

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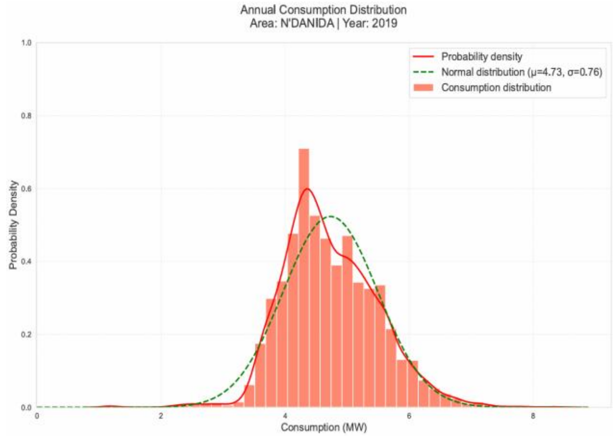

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Fig. 16: Graphs of changes in consumption for the year 2019 for all areas

The statistical results of electricity consumption for the year 2020 at each site are presented in Table 17.

Table 17: Statistical results by area for the year 2020

Statistical parameters											
Year	Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
2020	ADEWI	9149	2.632	2.491	2.112	0.726	8.000	1.023	0.845	0.522	-0.494
2020	ADIDOGOME	9149	3.606	3.498	3.300	0.264	9.867	0.841	0.488	1.574	11.351
2020	AVENOU	9149	3.655	3.465	3.300	0.726	9.933	0.904	0.596	1.996	7.261
2020	CASABLANCA	9149	3.254	3.135	2.640	0.264	6.732	1.042	0.850	0.244	-0.218
2020	DOGBEAVOU	8374	3.493	3.300	3.472	0.363	9.900	1.266	1.011	0.822	0.633
2020	GAKLI	9149	4.354	4.356	4.092	0.264	8.646	0.984	0.775	-0.370	1.064
2020	GARAGE CENTRAL	9149	2.598	2.475	2.310	0.264	6.765	0.777	0.558	1.519	4.503
2020	N'DANIDA	9149	4.476	4.570	4.950	0.264	9.537	1.011	0.711	-1.225	3.775

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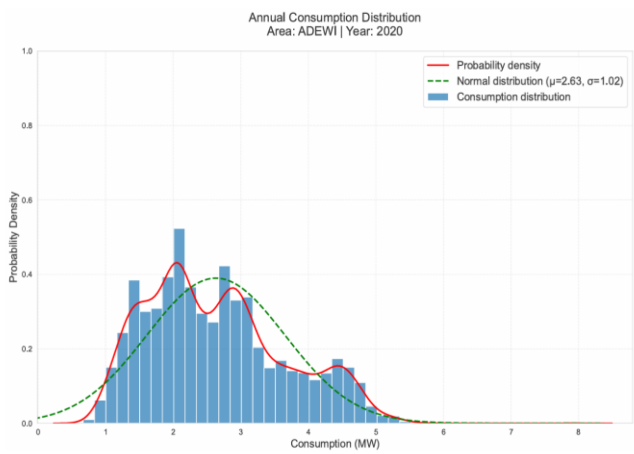
Figure17 shows the graphs of changes in electricity consumption at the eight sites for the year 2020.



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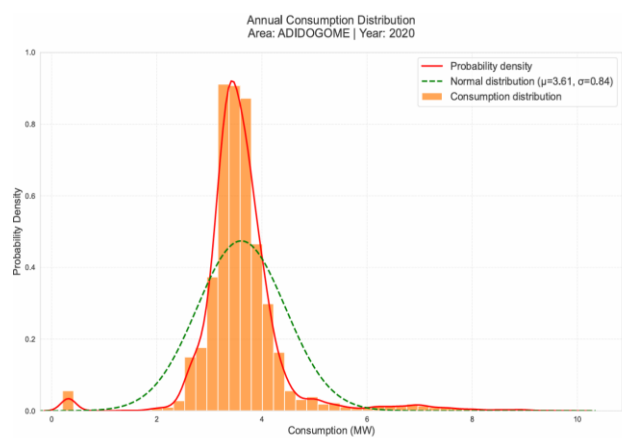

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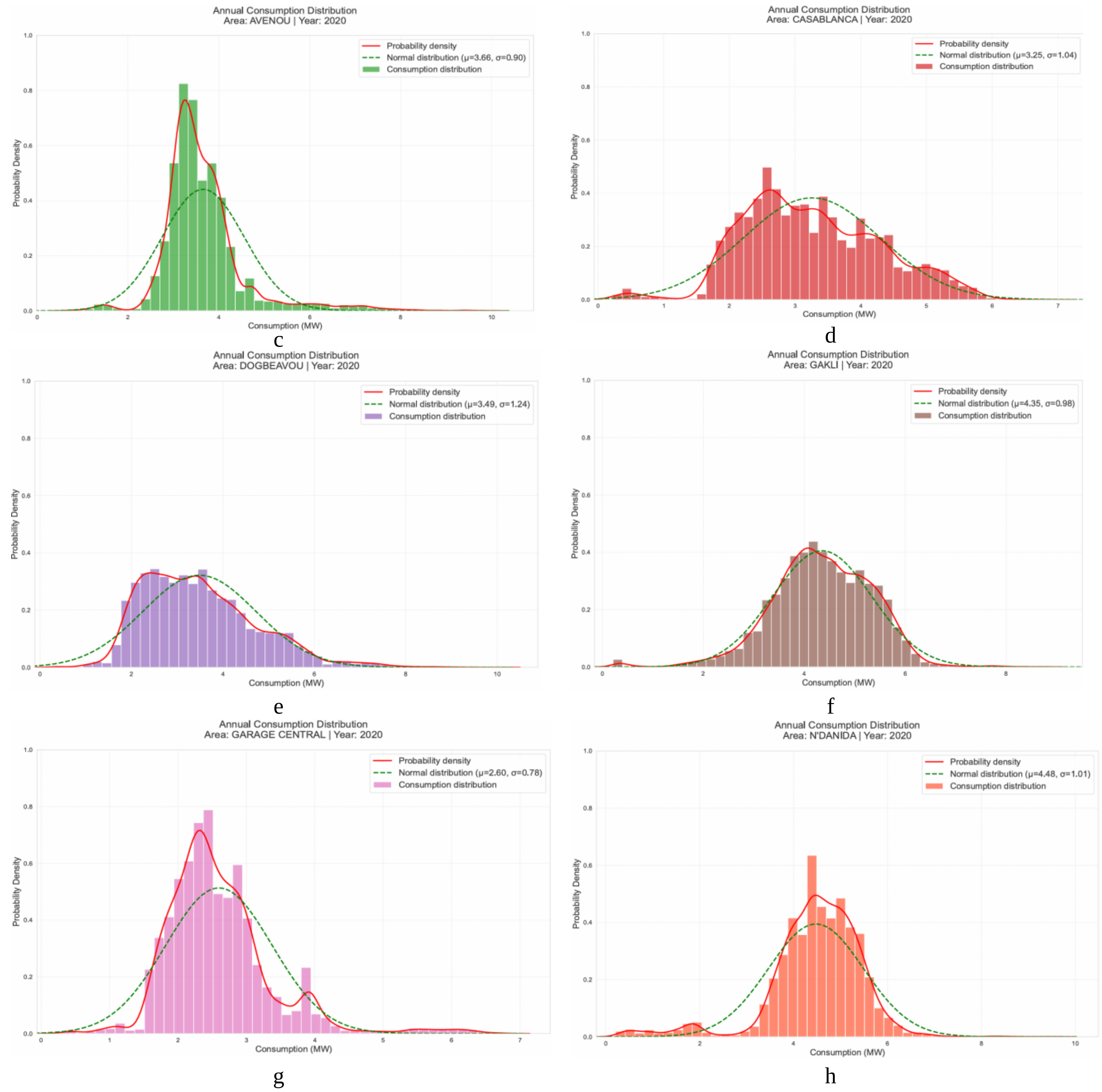

Fig. 17: Graphs showing changes in electricity consumption in 2020 for all areas

Table 18 presents the statistical results of electricity consumption at each site during the year 2021.

Table 18: Statistical results by area for the year 2021

Statistical Parameters											
Year	Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
2021	ADEWI	9169	2.852	2.588	2.409	0.495	9.400	1.083	0.889	0.636	0.159
2021	ADIDOGOME	9169	3.006	3.234	0.330	0.264	7.557	1.547	1.240	-0.672	-0.674
2021	AVENOU	9169	4.012	4.158	4.455	0.462	8.613	1.222	0.937	-0.064	0.478
2021	CASABLANCA	9169	3.448	3.300	3.182	0.330	5.874	0.950	0.785	0.212	-0.319
2021	DOGBEAVOU	8419	3.847	3.861	5.280	0.297	8.580	1.347	1.117	0.150	-0.228
2021	GAKLI	9169	4.130	3.993	4.719	0.264	8.514	1.505	1.201	-0.038	-0.219
2021	GARAGE CENTRAL	9169	3.419	3.102	2.970	0.264	8.283	1.329	1.064	0.724	0.173
2021	N'DANIDA	9169	3.149	3.564	3.960	0.264	6.567	1.044	0.930	-0.425	-0.913

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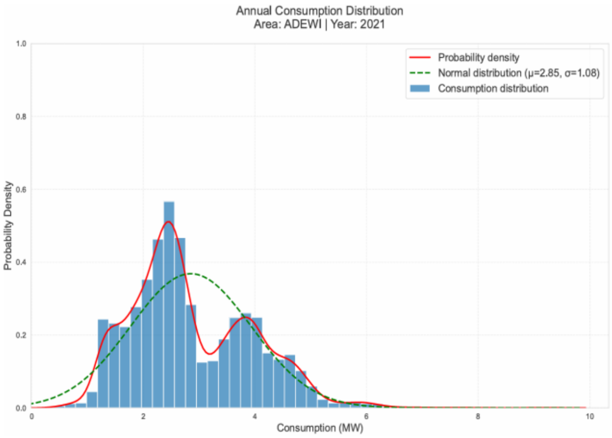
Figure 18 illustrates the distribution of electricity consumption at each site during the year 2021.



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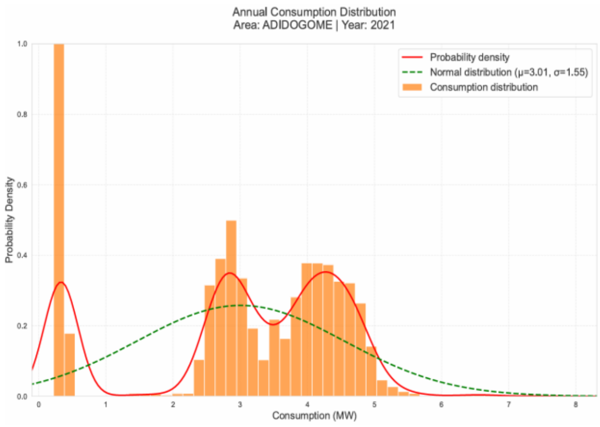

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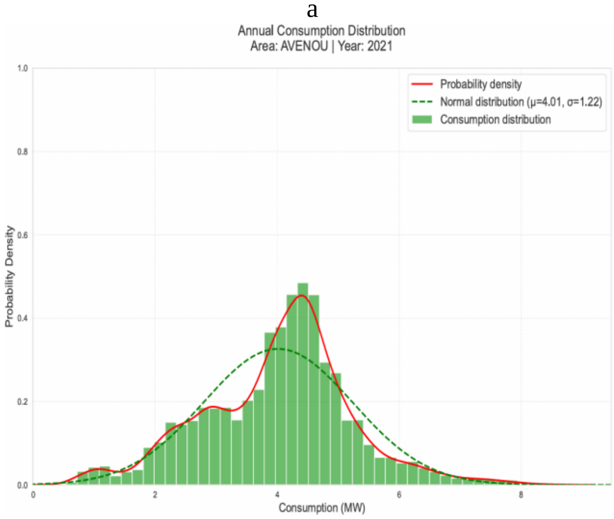

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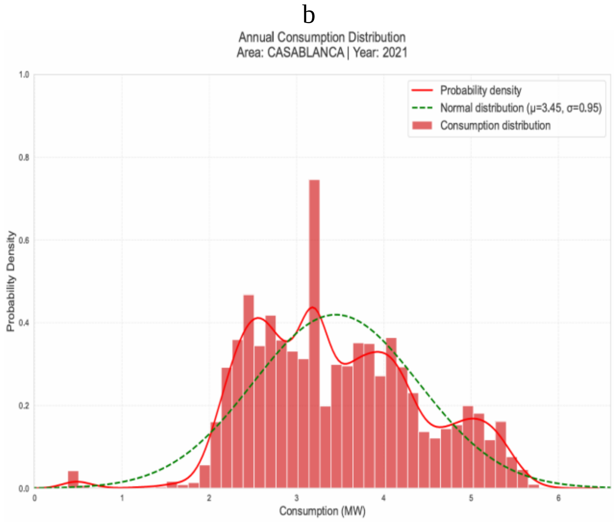

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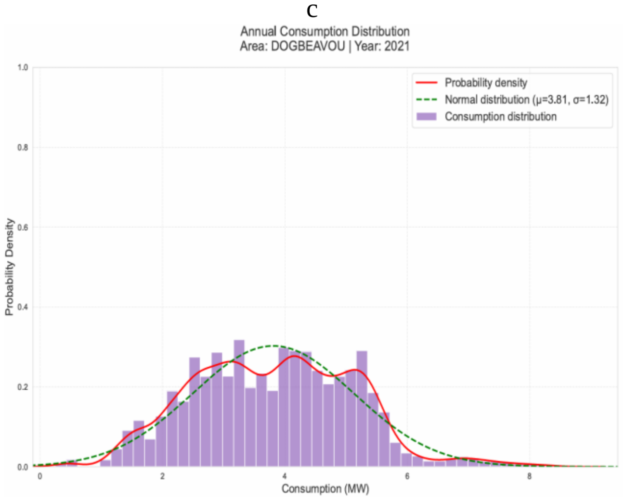

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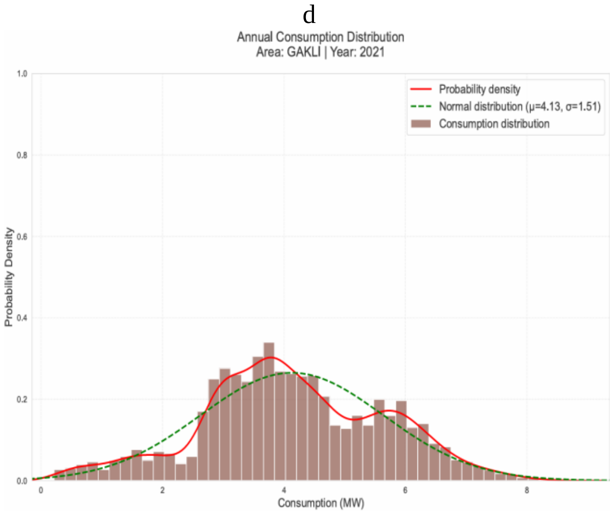

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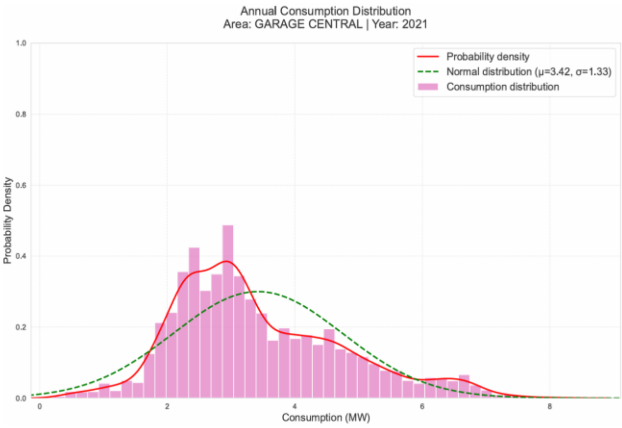

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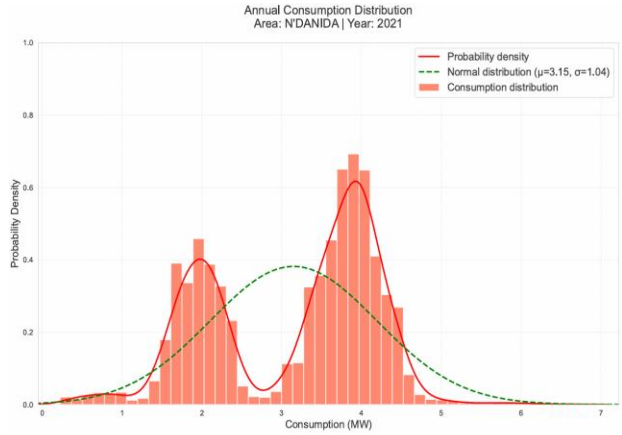

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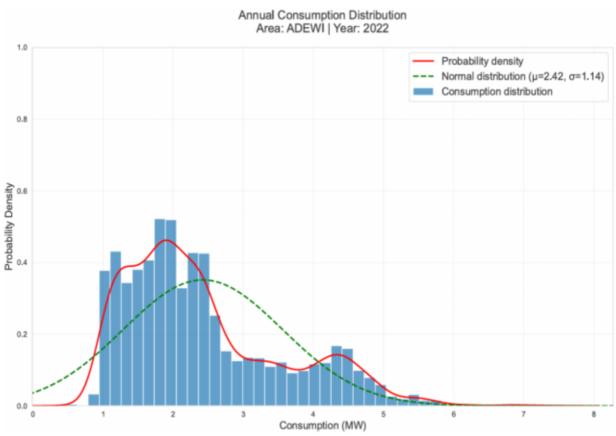
Fig. 18: Graphs showing changes in electricity consumption during 2021 for all areas

Table 19 presents the statistical results of electricity consumption at the eight sites for the year 2022.

Table 19: Statistical results by site for the year 2022

Tatistical Parameters											
Year	Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
2022	ADEWI	9132	2.424	2.112	1.980	0.528	7.524	1.135	0.903	0.967	0.264
2022	ADIDOGOME	9132	3.570	3.333	3.891	0.099	8.250	1.060	0.762	0.398	2.701
2022	AVENOU	9132	3.527	3.729	4.647	0.396	9.075	1.450	1.235	-0.032	-0.815
2022	CASABLANCA	9132	3.479	3.300	3.360	0.429	8.349	1.253	1.021	0.443	0.119
2022	DOGBEAVOU	8358	2.714	2.640	3.168	0.297	8.943	1.310	1.056	0.520	-0.015
2022	GAKLI	9132	4.512	4.620	4.389	0.297	9.000	1.223	0.958	-0.565	0.650
2022	GARAGE CENTRAL	9132	2.731	2.475	0.330	0.231	7.953	1.640	1.333	0.248	-0.674
2022	N'DANIDA	9132	3.399	3.366	3.036	0.231	7.600	0.539	0.420	0.533	2.602

Figure 19 illustrates the distribution of electricity consumption at each site during the year 2022.



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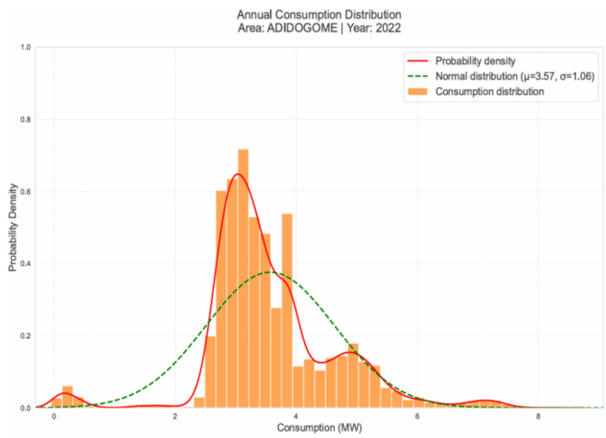

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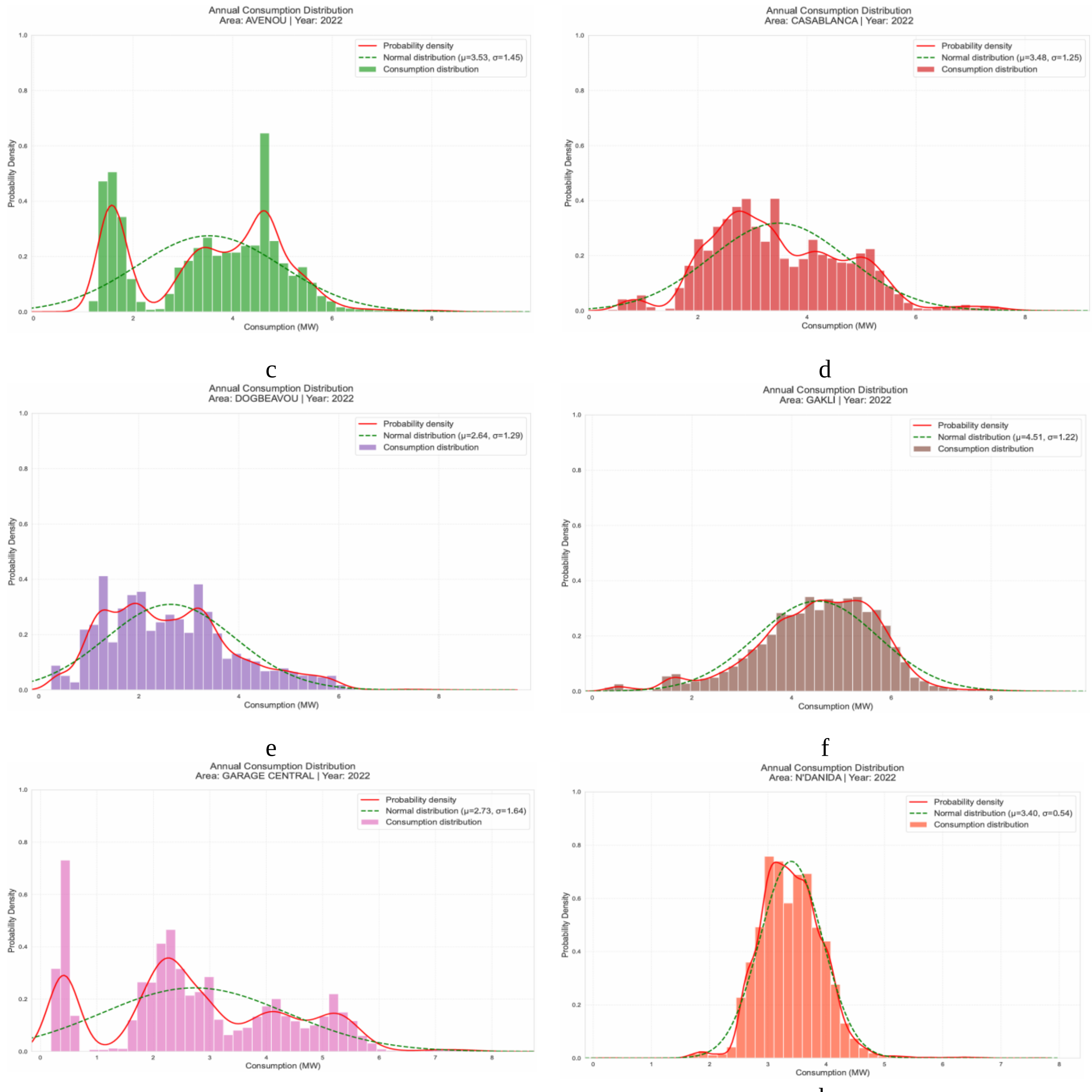

Fig. 19: Histograms of changes in electricity consumption at each site during the year 2022

The statistical results of electricity consumption at the eight sites for the year 2023 are presented in Table 20.

Table 20: Statistical results by area for the year 2023

Statistical Parameters											
Year	Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
2023	ADEWI	9298	2.247	2.244	2.310	0.825	5.775	0.850	0.616	1.168	1.885
2023	ADIDOGOME	9298	3.537	3.762	0.132	0.099	8.052	1.338	0.880	-1.130	1.959
2023	AVENOU	9298	4.243	4.059	3.498	1.155	8.778	1.077	0.828	0.570	0.711
2023	CASABLANCA	9298	3.660	3.399	3.212	0.627	6.798	1.183	0.998	0.208	-0.707
2023	DOGBEAVOU	8523	2.505	2.409	4.417	0.132	9.900	1.380	1.085	0.495	0.863
2023	GAKLI	9298	5.224	5.181	4.62	0.198	9.735	1.439	1.116	-0.179	0.995
2023	GARAGE CENTRAL	9298	4.088	4.125	3.762	0.231	8.415	1.003	0.779	-0.118	1.294
2023	N'DANIDA	9298	3.607	3.564	3.762	0.165	9.174	0.613	0.412	1.241	10.922

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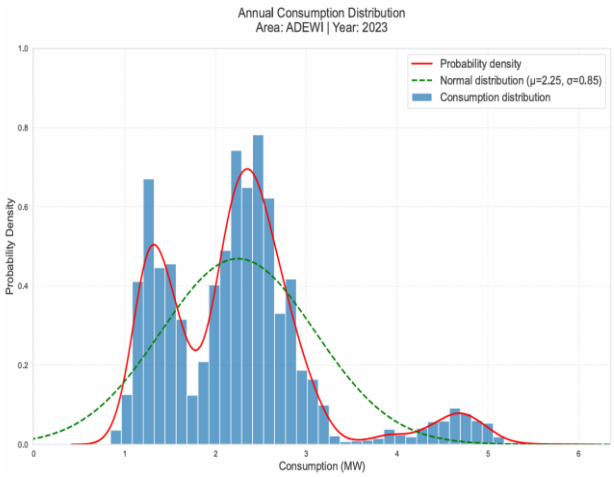
Figure 20 shows the evolution of electricity consumption during the year 2023 at each area.



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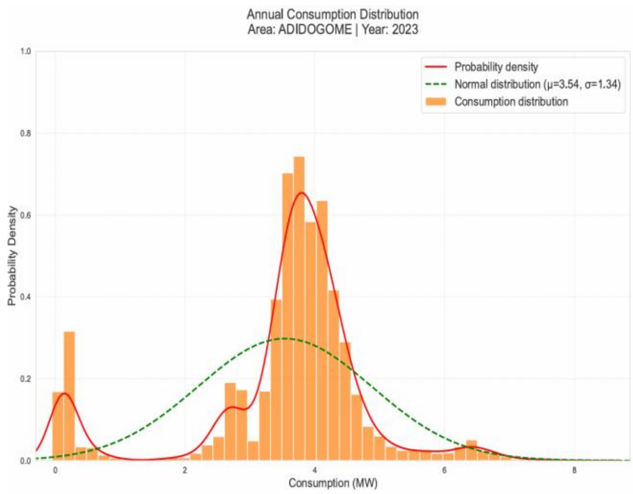

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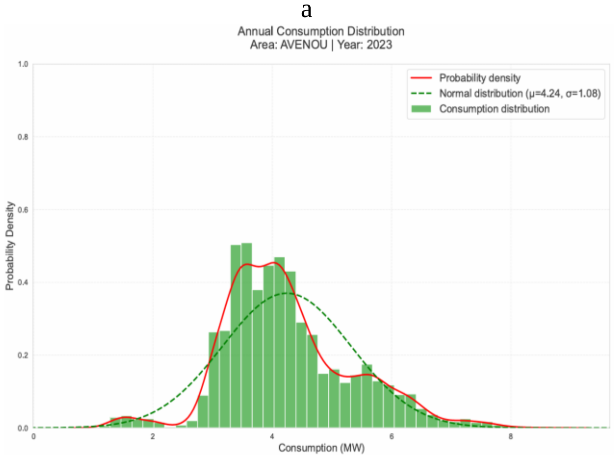

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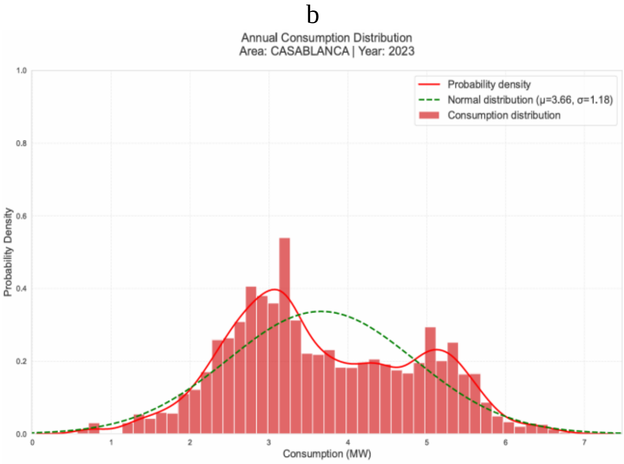

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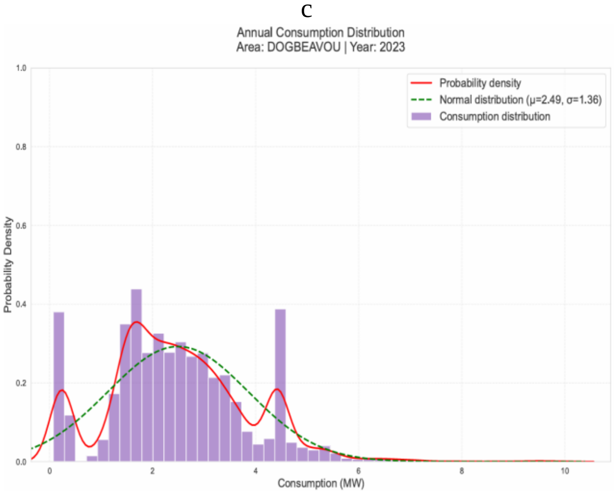

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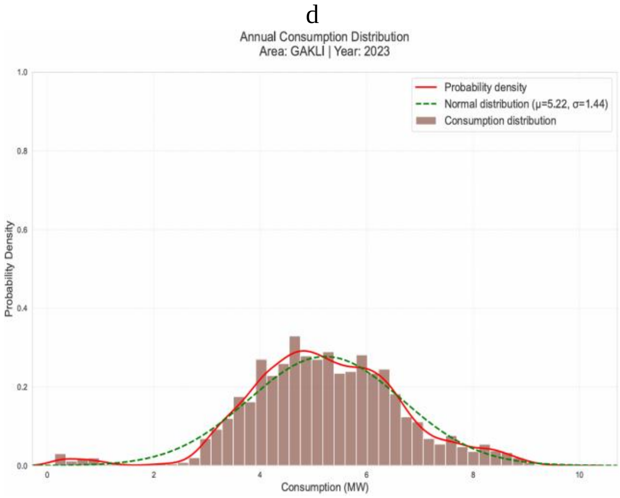

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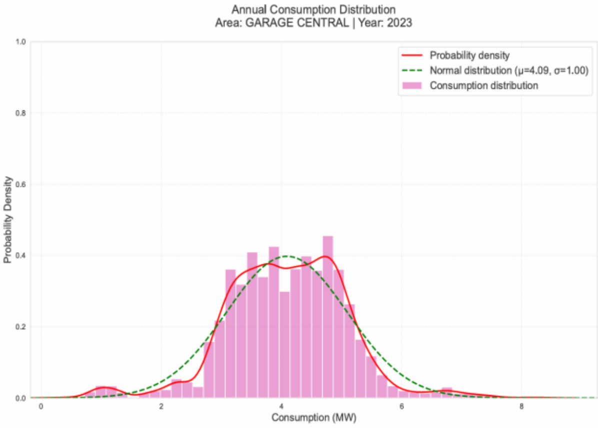

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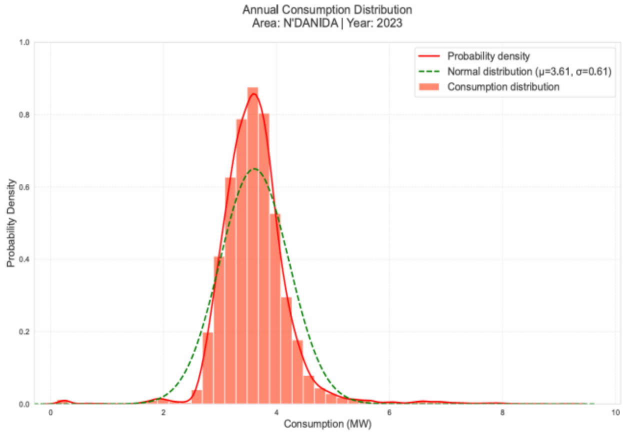

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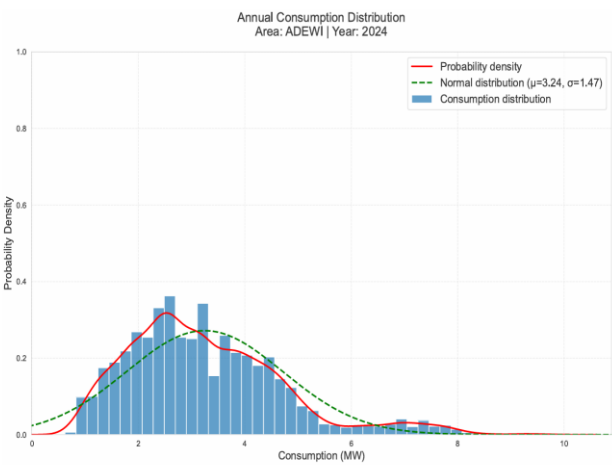
Fig. 20: Graphs of changes in electricity consumption for the year 2023 for all areas

Table 21 presents the statistical results of electricity consumption at each site during the year 2024.

Table 21: Statistical results by area for the year 2024

Statistical Parameters											
Year	Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
2024	ADEWI	8968	3.245	3.036	3.194	0.660	9.900	1.468	1.142	0.984	1.163
2024	ADIDOGOME	8968	0.715	0.132	0.132	0.099	7.689	1.492	0.995	2.348	3.948
2024	AVENOU	8968	5.620	5.808	6.270	0.099	9.405	1.485	1.030	-1.366	2.277
2024	CASABLANCA	8968	3.105	2.970	3.212	0.429	6.864	0.969	0.734	0.635	0.938
2024	DOGBEAVOU	8193	3.327	3.003	4.417	0.165	9.900	1.577	1.285	0.800	0.599
2024	GAKLI	8968	4.659	4.983	5.280	0.231	9.801	2.028	1.644	-0.302	-0.614
2024	GARAGE CENTRAL	8968	4.034	4.059	3.902	0.066	8.019	1.223	0.880	-0.502	1.454
2024	N'DANIDA	8968	4.116	4.158	3.960	0.297	9.240	0.842	0.586	-1.025	3.825

Figure 21 illustrates the evolution of electricity consumption at each site during the year 2024.



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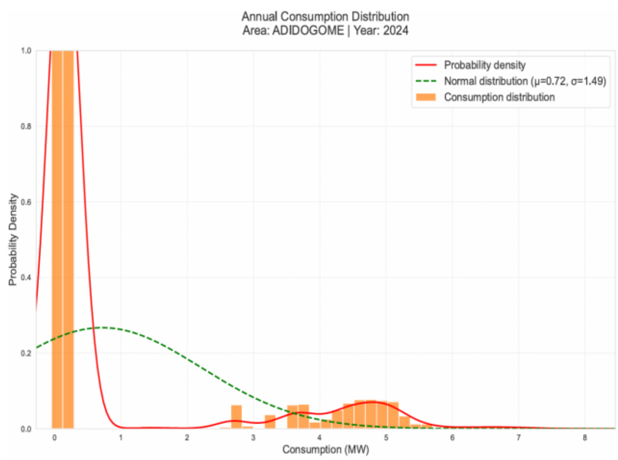

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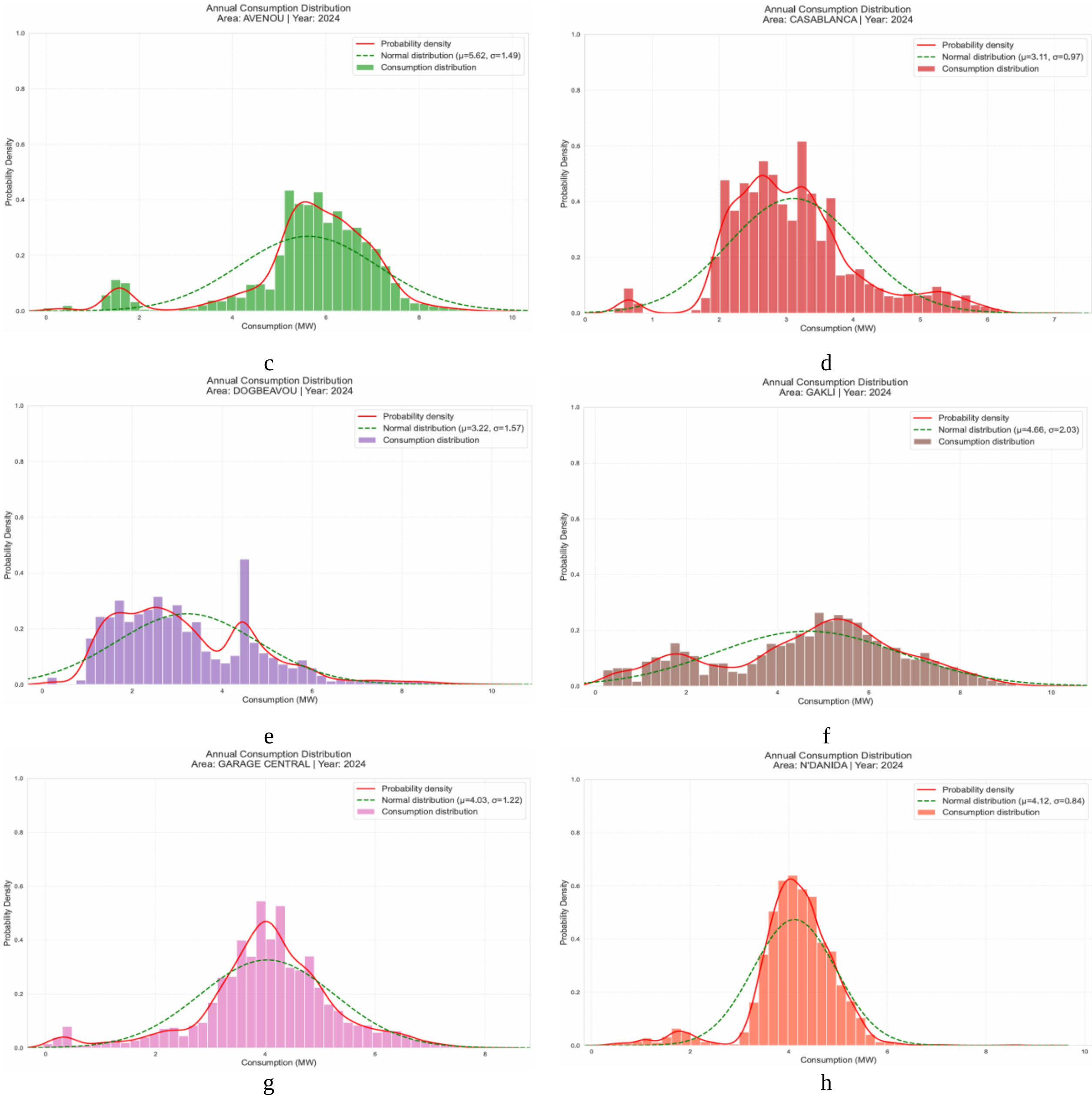

Fig. 21: Graphs showing changes in electricity consumption for the year 2024 for all areas

Table 22 presents the cumulative statistical results (7 years) of electricity consumption at each area.

Table 22: Cumulative statistical results for each area

Statistical Parameters										
Area	Count	Mean	Median	Mode	Min	Max	STD	MAD	Skewness	Kurtosis
ADEWI	63943	2.783	2.558	2.320	0.264	9.900	1.193	0.953	0.870	0.930
ADIDOGOME	63943	3.155	3.498	0.132	0.099	9.867	1.553	1.147	-0.707	0.243
AVENOU	63943	4.511	4.323	4.647	0.099	9.999	1.546	1.283	0.071	-0.462
CASABLANCA	63943	3.247	3.069	3.360	0.264	8.349	1.098	0.888	0.508	-0.037
DOGBEAVOU	58570	3.545	3.432	4.417	0.132	9.900	1.521	1.244	0.224	-0.223
GAKLI	63943	4.567	4.620	4.620	0.198	9.801	1.409	1.089	-0.181	0.614
GARAGE CENTRAL	63943	3.726	3.861	4.290	0.066	9.306	1.374	1.109	-0.184	-0.065
N'DANIDA	63943	4.056	4.059	3.960	0.165	9.537	1.023	0.781	-0.330	0.940

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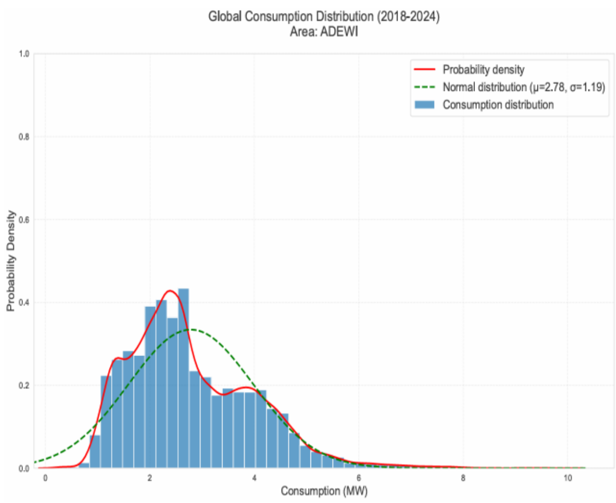
Figure 22 shows the evolution of electricity consumption at each site for the cumulative seven (07) years.



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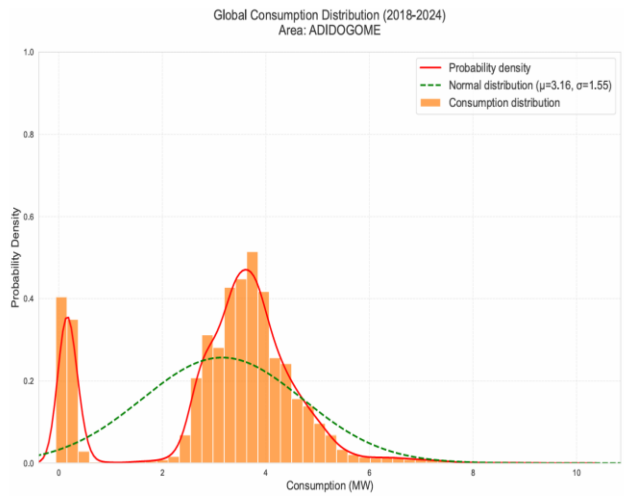

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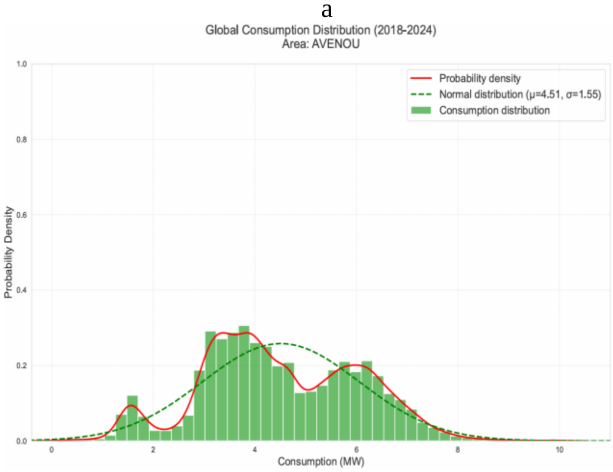

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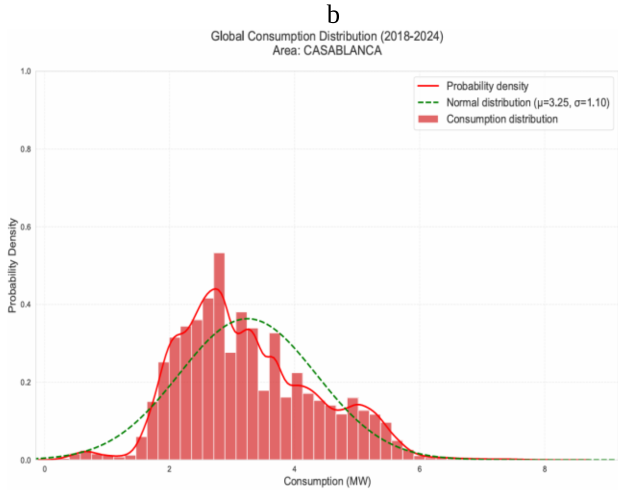

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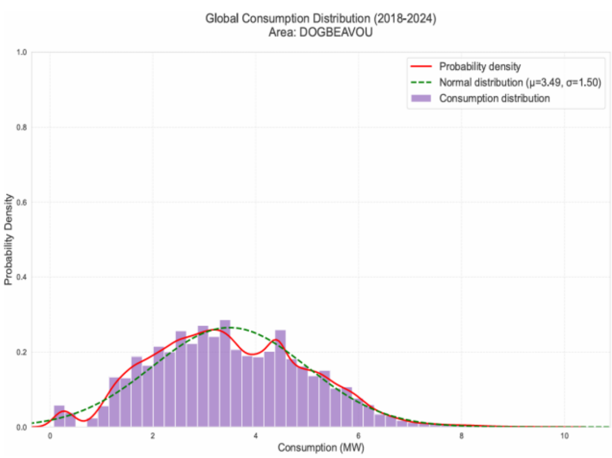

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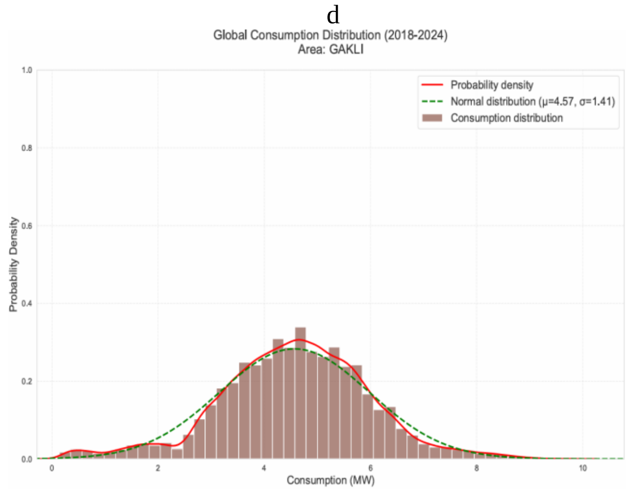

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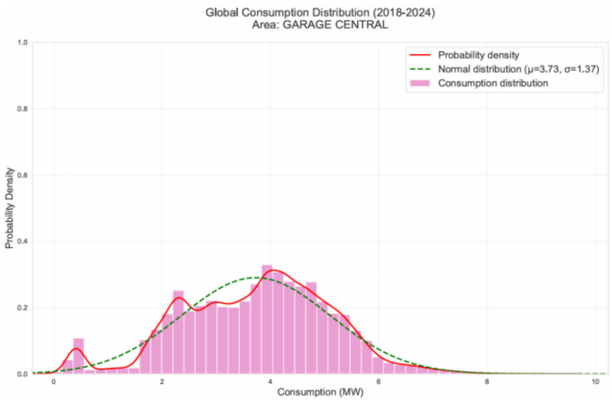

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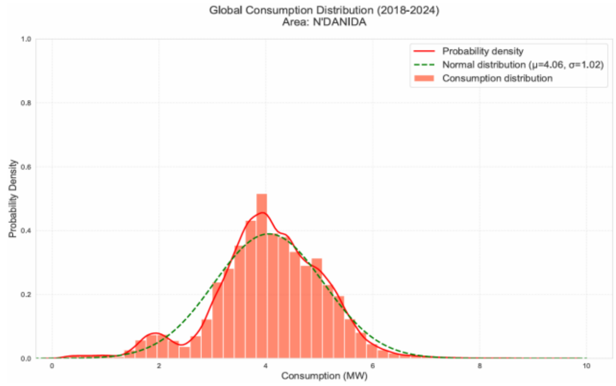

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Fig. 22: histograms of changes in electricity consumption on each site for the seven (07) cumulative years

Discussion

To understand a recurring situation and make optimal planning, the data must go through statistical analysis. Indeed, statistics is a scientific method that consists of observing and studying one or more common characteristics for a set of collected data (Lejeune, 2010). Unlike the latter, a statistic constitutes a number calculated from the data series (Hogg *et al*., 2015; Deisenroth *et al*., 2020). In the context of this work, the statistical study allowed us to calculate several numbers of the central tendency (Mean, median and mode); of the dispersion tendency (standard deviation and mean deviation) and of the shape tendency (Kurtosis and skewness). The results present three cases.

First, a good distribution (symmetrical distribution) around a central value. This is observed for the ADIDOGOME consumption series in the accounts for the months of January from 2018 to 2024 (Table 3). The average is 3.835 MW, the median is 3.891 MW, and the mode is 3.891 MW. The same is true for the AVENOU, DOGBEAVOU, and GARAGE CENTRAL areas during the same period. For example, mode = median = 3.300 MW for an average = 3.515 MW at the DOGBEAVOU site confirms this observation. This case is also observed at the CASABLANCA area for the months of November from 2018 to 2024 with: Average = 3.208 MW; median = mode = 3.212 MW (Table 13). Furthermore, for the year 2018 and at the ADIDOGOME, N'DANIDA, AVENOU, CASSABLANCA, and GARAGE CANTRAL areas, the graphs in Figs. 15b, Fig. 15h, Fig.15c, Fig. 15d, and Fig. 15g show a good evolution of the histograms in relation to the normal Gaussian distribution. Indeed, the normal distribution is symmetrical and bell-shaped on the histograms for a good distribution (Montgomery and Runger, 2014). The same situation can be seen for the year 2020 at AVENOU (Fig. 17c). The same is true for the GAKLI area over the seven-year period (2018-2024). This can be seen in Fig.22.f with: The mean = 4.567 MW; the median = 4.620 MW and the mode = 4.620 MW stored in Table 22. In this case, the installed power can be planned around the mean for sites that meet this distribution. Some previous studies (Zhaoyuan *et al*., 2025; Rocchetta, 2022; Jena and Sidharth, 2023) confirm this.

Next, we observe an asymmetrical distribution (median < mean: The mean is influenced by the high values in the data series) to the left of the central value. We observe this case for the ADIDOGOME area consumption series for the year 2024 (Table 21). We thus find 0.715 MW for the mean, the median is equal to 0.132 MW, and the maximum is 7.689 MW. The same is true for the DOGBEAVOU area during the same year (mean = 3.327 MW; median = 3.003 MW for a max = 9.900 MW), thus confirming our observation. These cases are also observed at the DOGBEAVOU (3.493 MW for the average, the median is equal to 3.300 MW and the max is 9.900 MW) and AVENOU (average = 3.655 MW; median = 3.465 MW for a Max = 9.933 MW) for the year 2020 (Table 17), further confirming our observation. The same is true for the GARAGE CENTRAL area (average = 3.419 MW; median = 3.102 MW and Max = 8.283 MW) for the year 2021 (Table 18). We can see this in Fig. 18g. This case of left-skewed distribution is more common at the ADEWI area. For example: (mean=3.049 MW; median = 2.623 MW for a Max = 6.996 MW) for the year 2019, see Table 15; (mean = 2.424 MW; median = 2.112 MW for a Max = 7.524 MW) during the year 2022, see Table 19. We also find: (Average = 3.060 MW; median = 2.706 MW for a Max = 8.349 MW) for the months of November from 2018 to 2024, See Table 13 and (average = 3.023 MW; median = 2.739 MW for a Max = 6.963 MW) for the months of October from 2018 to 2024, see Table 12. There are also two isolated cases of right-sided asymmetry. These are AVENOU for the year 2024 with: Median = 5.808 MW; mode = 6.270 MW; mean = 5.620 MW (Table 21). A similar situation is found in ADIDOGOME for the months of February from 2018 to 2024 with: Median = 3.960 MW; mode = 0.132 MW; mean = 3.685 MW (Table 3). These observations are confirmed by Fig. 21c and Fig. 4b. Given these irregularities, taking into account a fixed electrical power to be installed to meet the consumption needs of these sites requires further work.

Finally, a random distribution (neither symmetrical, nor asymmetrical to the left, nor asymmetrical to the right) around a central value. This is observed for the consumption series for the ADIDOGOME area for the months of August from 2018 to 2024. The average is 2.777 MW, the median is 3.333 MW, and the mode is 0.099 MW (Table 10). The same is true for the DOGBEAVOU and GARAGE CENTRAL areas during the same period. For example: Mean = 3.347 MW; median = 3.333 MW and mode = 2.277 MW at the GARAGE CENTRAL area confirm these cases of random distribution. In this study, these cases are more frequent at the ADIDOGOME area (mean = 3.554 MW; median = 3.927 MW and mode = 0.132 MW for the months of March from 2018 to 2024 (Table 5)). We have: Mean = 3.006 MW; median = 3.234 MW and mode = 0.330 MW during the year 2021 (Table 18). Then: mean = 3.623 MW; median = 3.960 MW and mode = 0.132 MW for the months of April from 2018 to 2024 (Table 6). After: Mean = 2.903 MW; median = 3.300 MW and mode = 0.132 MW for the months of November from 2018 to 2024, see Table 13. Subsequently: Mean = 3.306 MW; median = 3.696 MW and mode = 0.132 MW for the months of May from 2018 to 2024 (Table 7). We also find: Mean = 3.155 MW; median = 3.498 MW and mode = 0.132 MW for the seven cumulative years (Table 22). Then, for the months of July from 2018 to 2024, we find: Mean = 2.653 MW; median = 3.300 MW and mode = 0.099 MW (Table 9). Elsewhere, for the GARAGE CENTRAL area, we have: mean = 3.628 MW; median = 3.993 MW, and mode = 0.363 MW for the months of May from 2018 to 2024 (Table 7). Then, for the months of July from 2018 to 2024, we find: Mean = 3.080 MW; median = 3.267 MW and mode = 2.310 MW (Table 9). Similarly, for the months of March from 2018 to 2024 (Table 5), we have: Mean = 4.179 MW; median = 4.202 MW and mode = 4.202 MW. In the case of these types of random distributions, characterization presents many difficulties for decision-making. This necessitates, for the sites mentioned here, the use of artificial intelligence to determine the appropriate processing power. The work of Jhade *et al*. (2023); Mishra *et al*. (2019); Fay *et al*. (2021); Hassan *et al*. (2021) confirms this position.

Since the analysis of central tendencies did not allow us to rule on data mining for a fixed decision, the calculations are carried out on dispersion characteristics. Here, we used the standard deviation and the mean deviation. Indeed, the standard deviation is a measure of the dispersion of a statistical series around its mean. The more dispersed the distribution, the less the values are concentrated around the mean. In this case, the standard deviation will be high. Otherwise, it remains low or even zero. The lowest value of the standard deviation (0.539 MW) is observed on the N'DANIDA area for the year 2022 (Table 19) while it is 2.028 MW for the GAKLI site as the highest value for the year 2024 (Table 21). Through this work, we observe that the majority (more than 90%) of the standard deviation values are around 1 MW, making it possible to establish an approximation of 1 MW as the power margin to be installed in the areas considered. Observation confirmed by the work of (Zhaoyuan *et al*., 2025; Rocchetta, 2022; Jena and Sidharth, 2023).

Regarding the shape of a statistical data distribution, the calculation of skewness and kurtosis allows us to determine the observations. Skewness uses the power of 3 to measure the asymmetry around the mean, identifying tails that are shifted to the left or right. Kurtosis, using the exponent 4, measures the prominence of peaks and the weight of tails, giving more importance to extreme values. Unlike skewness, which is directional, kurtosis focuses on the magnitude of deviations. Theoretically, for a normal distribution, Skewness = 0 and Kurtosis = 3. In the context of the results presented by this work, kurtosis values around 3 are only seen at the GAKLI area (Table 5 and Table 16). Thus, we find kurtosis = 3.433 for the months of March 2018 to 2024; kurtosis = 3.651 during the year 2019 for the GAKLI site. Kurtosis values around 3 are observed at the N'DANIDA and ADIDOGOME areas with: a kurtosis = 2.811 for the months of December from 2018 to 2024 on the N'DANIDA area (Table 14) and a kurtosis = 2.510 during the year 2019 for the ADIDOGOME area (Table 16). Regarding skewness, the more symmetric the data are, the closer it is to zero. In the case of our study, the skewness value closest to zero is observed at the CASABLANCA area (skewness = 0.009, see Table 5) in the months of March from 2018 to 2024. Other skewness values close to zero are also found at the AVENOU areas (skewness = 0.013 for the months of June from 2018 to 2024 (Table 8); skewness = 0.064 for the year 2021 (Table 18) and skewness = 0.071 for the seven cumulative years (Table 22)); of GAKLI (skewness = 0.038 for the account of the year 2021 (Table 18)) and skewness = 0.044 for the months of June from 2018 to 2024 (table 8); of N'DANIDA (skewness = 0.014 for the account of the months of October from 2018 to 2024 (Table 12)); of GARAGE CENTRAL (skewness = 0.042 for the account of the months of December 2018 to 2024 (Table 14)); skewness = 0.045 for the account of the months of September from 2018 to 2024 (Table 11); skewness = 0.079 for the account of the months of January from 2018 to 2024 (Table 3); skewness = 0.090 for the account of the months from November 2018 to 2024 (Table 13) and skewness = 0.092 for the account of the months from April 2018 to 2024 (Table 6)) and DOGBEAVOU (skewness = 0.046 for the account of the months from June 2018 to 2024 (Table 8). By the way, kurtosis and skewness help us understand the symmetry and concentration of values relative to the mean. In the context of our results, skewness and kurtosis do not provide us with in-depth information on the distribution of the data because they are very rare around their normalized values. This does not make them essential for understanding the nuances of our data and does not make it easier for us to choose the necessary and sufficient electrical power to produce to meet the consumption needs of the explored areas. The

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work of Blanca *et al*. (2020); Thomas *et al*. (2020) confirms our position.

On the eight (08) areas, the consumption peaks are between 5.643 and 9.900 MW. The average consumption is between 2.800 and 5.620 MW. Furthermore, we note that the areas of ADIDOGOME, DOGBEAVOU, CASABLANCA and GARAGE CENTRAL have similar average consumption patterns with values often between 3.000 and 3.700 MW. Similarly, the areas of AVENOU, GAKLI and N'DANIDA have almost identical average consumption profiles of around 4.000 and 5.000 MW. The average consumption of the ADEWI area is generally between 2.000 MW and 3.000 MW, making it low compared to the other seven areas. However, in 2024 the ADIDOGOME site shows an unusual average consumption. We observe an average consumption of 0.715 MW for a max = 7.689 MW, i.e., an average consumption decreases of 79.78% compared to that of the year 2023 (Tables 20 and 21). It becomes the lowest average consumption recorded in this study for all areas and all periods combined. Furthermore, during the period from May to August from 2018 to 2024, there is a decrease in average consumption and peak consumption at almost all sites compared to that of the period from September to November and that of the period from December to April from 2018 to 2024. There is also a slight increase in average consumption during the period from December to April from 2018 to 2024 compared to that observed during the period from September to November.

Conclusion

This study presents an approach based on the statistical analysis of available data to evaluate the consumption of electrical energy by municipality. To achieve this, this study takes into account eight (8) areas of three municipalities distributed in the administrative region of greater Lome, namely: ADEWI and GARAGE CENTRAL of the municipality of Golfe 3; DOGBEAVOU and N'DANIDA of the municipality of Golfe 4 and: ADIDOGOME, AVENOU, CASABLANCA and GAKLI of the municipality of Golfe 5. The consumption data (power in MW) of the eight (08) sites for 84 months (7 years), from January 1, 2018 to December 31, 2024 provided by the Togo Electric Energy Company (CEET), Lomé A station, served as materials to develop this work. In total, 63,943 samples per area were processed. As a method, a statistical characterization on the active power consumed is carried out, taking into account: The mean; the median; the mode; the Max and the Min; the standard deviation; the mean deviation; the Skewness and the Kurtosis. The results reveal three distinct distribution profiles: Symmetric, asymmetric and random around a central value. However, skewness and flattening do not provide us with in-depth information on the data distribution because they are very rare around their normalized values. Regarding the dispersion, we observe that the majority (more than 90%) of the standard deviation values revolve around 1 MW, allowing us to establish an approximation of $\pm$ 1 MW as the power margin to be installed in the considered areas.

Taking these results into account, the characterization of consumption reveals the importance of statistical analysis of available data to assess electrical energy consumption by municipality. However, we find ourselves with difficulties in choosing the electrical power to install due to the distribution of data in relation to the statistical metrics used. The call for more in-depth studies is required by exploitation and exploration of models to achieve optimization. All things considered, the achievement of the development of municipalities must initially involve an increase in electricity needs and the autonomy of its production based on available primary sources, it is necessary to establish a necessary electrical power consumed by each. The rest will be the decisions and regulations necessary for its achievement.

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Author's Contributions

Krou Iparbè: Study design, writing of simulation codes, data analysis, then writing of the manuscript.

Apaloo Bara Komla Kpomonè: Monitoring of the work, critical revision of the manuscript and constructive suggestions for its improvement.

Palanga Eyouleki Tcheyi Gnadi: Monitoring of the work, critical revision of the manuscript and constructive suggestions for its improvement.

Baraté Mohamed: Revision of the summary by improving it and then adapting it to the content, following his critical contribution as a reviewer and his series of questions allowing an understanding of the manuscript based on the work carried out.

Baba Kpatchaa Tombana: Critical revision and proofreading of the manuscript and constructive suggestions for its improvement.

Lamboni Yendoubouame: Revision of the summary by improving it and then adapting it to the content, following his critical contribution as a reviewer and his series of questions allowing an understanding of the manuscript based on the work carried out.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all other authors have read and approved the manuscript and that no ethical issues are raised.

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